



THE UNIVERSITY *of* EDINBURGH

## Edinburgh Research Explorer

### The U-shapes of occupational mobility

**Citation for published version:**

Groes, F, Kircher, P & Manovskii, I 2015, 'The U-shapes of occupational mobility', *The Review of Economic Studies*, vol. 82, no. 2, pp. 659-692. <https://doi.org/10.1093/restud/rdu037>

**Digital Object Identifier (DOI):**

[10.1093/restud/rdu037](https://doi.org/10.1093/restud/rdu037)

**Link:**

[Link to publication record in Edinburgh Research Explorer](#)

**Document Version:**

Early version, also known as pre-print

**Published In:**

The Review of Economic Studies

**Publisher Rights Statement:**

© Groes, F., Kircher, P., & Manovskii, I. (2015). The U-Shapes of Occupational Mobility. Review of Economic Studies, 82(2), 659-692. 10.1093/restud/rdu037

**General rights**

Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

**Take down policy**

The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact [openaccess@ed.ac.uk](mailto:openaccess@ed.ac.uk) providing details, and we will remove access to the work immediately and investigate your claim.



# The U-Shapes of Occupational Mobility\*

Fane Groes  
Copenhagen Business School

Philipp Kircher  
University of Edinburgh and London School of Economics

Iouri Manovskii  
University of Pennsylvania

## Abstract

Using administrative panel data on the entire Danish population we document a new set of facts characterizing occupational mobility. For most occupations, mobility is U-shaped and directional: not only low but also high wage earners within an occupation have a particularly large probability of leaving their occupation, and the low (high) earners tend to switch to new occupations with lower (higher) average wages. Exceptions to this pattern of two-sided selection are occupations with steeply rising (declining) productivity, where mainly the lower (higher) paid workers within this occupation tend to leave. The facts conflict with several existing theories that are used to account for endogeneity in occupational choice, but it is shown analytically that the patterns are explained consistently within a theory of vertical sorting under absolute advantage that includes learning about workers' abilities.

**JEL Classification:** E24, E25, J24, J31

**Keywords:** Occupational mobility, Learning, Labor markets, Sorting, Comparative and Absolute Advantage

---

\*First version: June 2008. This version: February 2014. We would like to thank the editor and two anonymous referees for their comments and suggestions. We are also grateful to Martin Browning, Mette Ejrnæs, Pieter Gautier, Jonathan Heathcote, Hans Christian Konsted, Dale Mortensen, Giuseppe Moscarini, Theodore Papa-georgiou, Kjetil Storesletten, and seminar participants at the University of Copenhagen, Copenhagen Business School, University of Essex, University of Maryland, the Minneapolis Fed, University of Oxford, University of Southampton, the 2008 Copenhagen Microeconometrics Summer Workshop, the Search & Matching workshop at the University of Pennsylvania, 2009 NBER Summer Institute, 2009 Society for Economic Dynamics annual meeting, 2009 Macroeconomics across Time and Space conference, 2009 Econometric Society European meeting, and 2010 Lincoln College Applied Microeconometrics conference for their comments. This research has been supported by the National Science Foundation Grant No. SES-0922406 and the European Research Council Grant No. 284119.

# 1 Introduction

Danish employers report that every year close to a fifth of the their workers change occupations (e.g., technician, engineer, manager). Similar levels of occupational mobility are reported for the US.<sup>1</sup> Moreover, these gross flows are much larger than the net flows that are needed to account for the changing sizes of occupations. What induces workers to undertake these occupational changes? The answer to this question seems especially interesting because occupational choices and wages are closely related. First, the differences in average occupational wages are substantial and persistent. Second, it has recently been argued that the returns to occupational tenure are nearly as large as the returns to labor market experience and much larger than the returns to firm or industry tenure.<sup>2</sup> Thus, understanding workers' occupational choices is important for understanding the allocation of the labor force across productive activities, for interpreting earning patterns, for measuring the returns to human capital accumulation, and for assessing the effects of various policies affecting sorting of workers across occupations. Since occupational choices are endogenous, the outcome of such analysis will depend on the theory used to account for selection of workers across occupations. While there exist a number of theories of occupational choice, it remains an open empirical question which selection process is consistent with the data.

This paper contributes to our understanding of selection in occupational choices by looking at occupational mobility data in a novel way. Using administrative data on 100% of the Danish workforce we provide new direct evidence on patterns of worker mobility across occupations. This evidence conflicts with several existing theories that are often used to account for the endogeneity in occupational choice, but we can show analytically that the patterns are explained consistently within a theory of vertical occupational mobility combined with learning about worker ability.

We document that for most occupations, mobility is U-shaped and directional: it is both the low wage and the high wage workers *within an occupation* who have a particularly large probability of leaving that occupation, while the lowest probability of leaving is associated with the medium wage workers within the occupation. More than three-quarters of the labor force are employed in occupations exhibiting this pattern. While switching probabilities are particularly high at both ends of the wage spectrum within an occupation, the direction of sorting is very different for high and low wage earners. Those earning low wages relative to other workers in the same occupation tend to leave for new occupations that on average pay less to their workforce than the old occupation, while those with high relative wages in their occupation tend to leave for occupations that on average pay more to their workforce. These patterns remain whether we focus

---

<sup>1</sup>See Kambourov and Manovskii (2008) and Moscarini and Thomsson (2007).

<sup>2</sup>See Shaw (1984, 1987), Kambourov and Manovskii (2009b), Groes (2010), among others.

on workers who stay with the same firm or on those who switch firms, and across various ways of defining occupations. The U-shaped mobility pattern is predominant except for occupations with steeply rising (declining) productivity, from which mainly the lower (higher) paid workers tend to leave.

We are able to document these patterns because the data allow us to compare the behavior of different workers in the same occupation. Such analysis has been missing in the literature partly because most longitudinal datasets that have traditionally been analyzed feature only panels of a few thousand workers, and with around three hundred occupations, an analysis on a per occupation basis was not feasible. This new look at the data has at least two important direct implications: First, selection is not just one-sided. In particular, the well documented wage growth with tenure in an occupation is not just due to low wage earners leaving and high wage earners staying. In fact, a large number of high wage earners are leaving their occupations as well, and models generating the wage implications based on worker selection need to take this into account. Second, occupations with strong productivity growth nevertheless shed a large fraction of their workforce, a stark feature of the data not featured by the commonly used models.

A number of prominent models of occupational choice feature counter-factual one-sided selection, typically with relatively low wage earners leaving the occupation while high wage earners stay. One popular class of such models is based on horizontal sorting due to match-specific shocks. Originating from Jovanovic (1979) and extended to occupational mobility by, e.g., McCall (1990) and Neal (1999), this work is based on the idea that occupations are identical (e.g., not different with respect to skill requirements), but workers find out the quality of their idiosyncratic match with an occupation over time. Horizontal re-sorting occurs when workers realize that their match-specific productivity is low and abandon the match in favor of (the search for) a better one. Thus, the model predicts that workers with low wages (low quality matches) leave the occupation, and their next occupational choice is a random draw. Both predictions do not match up with our findings in the data. Similarly, island economy models based on human capital extensions of Lucas and Prescott (1974), such as Kambourov and Manovskii (2005) and Alvarez and Shimer (2009), typically predict that it is the low human capital and hence, low wage, workers who are the first to switch if occupational demand declines since high human capital workers have more incentive to wait for the conditions to improve. If occupational demand rises, no one leaves the occupation. The wage a switcher obtains in the new occupation is independent of her relative wage in the previous occupation. Once again, these implications do not match up with the patterns we find in the data.

Nevertheless, we show theoretically that selection based on vertical sorting where more able workers are matched with more productive occupations does account well for all of the qualitative

empirical patterns: High-ability workers within an occupation tend to earn high wages, and changes to their perceived ability can lift them beyond the threshold where it is optimal to move to a more skill-intensive occupation, inducing (predominantly) upward mobility. Workers whose perceived ability is such that they obtain wages close to the middle of the occupational wage distribution are less likely to update their beliefs sufficiently to warrant a move to a new occupation, so their mobility is lower. Low-ability workers within an occupation tend to earn lower wages and changes to their perceived ability might induce them to move to an occupation with lower skill-requirements, inducing (predominantly) downward mobility. While there are many reasons why perceived ability may be changing (some are discussed below), one plausible reason is that workers' ability gets revealed only slowly over time through observations of labor market performance, as formalized in the decision-theoretic work of Gibbons and Waldman (1999) that was successfully used to understand mobility and promotion dynamics within firms. Our model is an extension of this framework to a general equilibrium setting where wages are set in competition for workers. This is similar to Papageorgiou (2012), although we abstract from a number of elements (search frictions, differential speed of learning) to be able to provide a clear and easily comprehensible insight on sorting across many occupations.

In addition to accounting for the qualitative U-shaped mobility patterns and the direction of switching, this theory also has secondary implications that conform well with the data. Considering occupations with roughly constant productivities, the theory predicts that workers who switch to occupations with higher average wages see faster wage growth than workers who stay, who, in turn, see faster wage growth than workers who move to occupations with lower average wages. In terms of wage levels, those who switch to an occupation with higher average wages do better than those who remain in the old occupation, but worse than those who already work in the new occupation. The opposite holds for workers that move occupations with lower average wages. Older workers switch occupation less frequently, and their wage-distribution is more dispersed than that of younger workers. Finally, the equilibrium nature of the model implies that occupations with sharply increasing productivity will retain their high earners but shed their low earners, and the opposite holds for occupations with a substantial decline in productivity.

Therefore, vertical re-sorting as a consequence of changes in perceived ability seems a promising avenue to account and control for endogenous occupational mobility. This view of the labor market has a long tradition, even though in the context of occupational mobility horizontal sorting and match-specific shocks have arguably received more attention. Vertical sorting is a basic feature of the famous Roy (1951) specification with absolute advantage, and its combination with learning about workers' permanent ability has been explored, e.g., in Johnson (1978), Miller (1984), Gibbons and Katz (1992), Jovanovic and Nyarko (1997), Gibbons and Waldman (1999),

and Papageorgiou (2012). We discuss the similarities and the differences from the Roy (1951) model explicitly.<sup>3</sup> The main distinguishing feature arises in the presence of occupational productivity shocks, where decision-theoretic models imply that a rising occupational productivity will make the occupation more attractive for all workers, while in our equilibrium model it becomes more attractive only for the more productive workers who compete with and drive out the less able workers. In contrast to other equilibrium models, the main advantage of our formulation is its simplicity, which allows us to easily handle many occupations which is necessary to derive many of the important results.<sup>4</sup> In line with all the work cited in this paragraph, we abstract from an explicit notion of firms. Our main reason is that in the data the pattern of occupational switching is similar for workers who stay with the same firm as for those who switch firms.<sup>5</sup>

In the next section we present our key empirical findings that occupational switching is U-shaped and directional, the main indicators that suggest the use of the absolute advantage model that we outline in Section 3. In the initial theoretical part we stay deliberately simple in order to present a theory on the same level of tractability as existing work on learning under horizontal sorting. We show that the model conforms well with the basic facts and its additional predictions also match up with the data. In Section 4 we extend the model to allow for changing occupational productivity, and confront its implications with the data.

Due to space limitations, we discuss a number of extensions of the model and various alternative explanations for our findings in the Appendix available online. In particular, in Appendix OA14 we introduce specific and general human capital accumulation into the model. General human capital accumulation helps the model match the observation that on average workers switch to more productive occupations with age. While we show that the model with human capital accumulation tends to feature similar patterns of mobility as our simpler benchmark model, these extensions will likely be important for future work that will incorporate the selection model that we propose in the empirical investigation of wage and human capital accumulation patterns. We also highlight existing econometric techniques that might be suitable given our analysis. While vertically differentiated view of occupations appears key to explaining why high-wage workers within an occupation switch more than medium-wage workers, in the Appendix we discuss that

---

<sup>3</sup>We compare our model to the simplest and most popular in applied work version of the Roy model - a comparison that we think has substantial pedagogical merit. We also abstract from the presence of search frictions, introduced into the Roy model by Moscarini (2001), which help explain the excess of gross over net mobility.

<sup>4</sup>U-shapes arise in the model only for intermediate occupations, where less able workers can leave for lower ranked occupations and more able worker can switch to better ranked occupations. With only two occupations, high ranked workers in the top occupation have no-where better to go and low-ranked workers in the bottom occupation again have no-where lower to go, which limits mobility and allows only for one-sided selection.

<sup>5</sup>Our analysis in Section 2.4.2 and Appendix OA14.4 suggests that firm affiliation might not be of first order importance for understanding the basic patterns of occupational mobility.

learning about ability is only one possible determinant of occupational mobility. For example, human capital accumulation alone provides an alternative explanation for upward occupational mobility, but since a non-trivial fraction of workers experience downward occupational mobility both within and across firms it would have to be combined with another element. Learning implies that workers sometimes find out that they are less able than anticipated, but general shocks to workers' ability would provide another plausible explanation. Both have very similar implications, but the former gives a more natural reason why older workers change occupations less. In the Appendix we also discuss the role of compensating differentials and the connection of our theory with the literature on the internal labor markets within firms.

The main message of this paper concerns the nature of occupational selection. Selection at the bottom of the within-occupation wage spectrum has long been emphasized and is very intuitive: Low wages are an indication that a person should be doing something else, who therefore has a tendency to leave the occupation. If that were the only source of selection, in the cross-section wages would increase with occupational tenure simply because only high-wage earners stay. In contrast, we highlight that selection is equally strong at the top of the within-occupation wage spectrum. This suggests that high wages are *not* a sign that a person is particularly well matched in his current occupation: in a world with vertically differentiated occupations we show that this is rather a sign of overqualification that induces workers to seek more suitable types of work. If this is the case, the dominant direction of mobility of high earners should be different from that of low earners, which is consistent with the pattern we document in the data. Of course, we do not think that the simple vertical sorting mechanism that we propose accounts for the full extent of occupational mobility. In the Conclusion we discuss the broader research agenda, and the challenges to the empirical assessment of the exact quantitative implications of the patterns presented in this paper. Both vertical and horizontal moves likely arise in the labor market, i.e., some occupations are considered better than others while some are just different and people switch along both of these dimensions (for example, in a complementary work Papageorgiou (2011) finds evidence of substantial horizontal worker sorting across three broad occupational categories based on the comparative advantage). And among those occupations that can be ranked as better or worse, the ranking might change over time. Therefore, it is likely that match-specific components and the volatility of productivities of occupations or of the demands for their services are responsible for a nontrivial share of mobility. An important part of a future agenda is to identify which occupations form vertical hierarchies in order to identify the costs of switching within and across hierarchies. Our analysis suggests that many of the occupational switches do arise within hierarchies. Therefore, we do think that the mechanism we emphasize should be an important part of any comprehensive theory of occupational mobility.

## 2 The U-shapes of Occupational Mobility: Evidence

### 2.1 Data

We use the administrative Danish register data covering 100% of the population in the years 1980 to 2002. The first part of the data is from the Integrated Database for Labor Market Research (IDA), which contains annual information on socioeconomic variables (e.g., age, gender, education, etc.) and characteristics of employment (e.g., private sector or government, occupations, industries, etc.) of the population. Information on wages is extracted from the Income Registers and consists of the hourly wage in the job held in the last week in November of each year. Wage information is not available for workers who are not employed in the last week of November. The wages are deflated to the 1995 wage level using Statistics Denmark's consumer price index and trimmed from above and below at the 0.99 and 0.01 percentile for each year of the selected samples described below.

We use the Danish rather than the U.S. data for two reasons. First, the sample size is much larger. Our objective is to document the patterns of occupational mobility depending on the position of the individual in the wage distribution within her occupation. A sample sufficiently large to be representative *in each occupation* is essential for this purpose. Second, the administrative data minimizes the amount of measurement error in occupational coding that plagues the available U.S. data (see Kambourov and Manovskii (2009b)). Nevertheless, we find that the features of occupational mobility that can be compared between the U.S. and Denmark are quite similar.<sup>6</sup> This leads us to expect that the patterns of occupational mobility that we describe using Danish data generalize to, e.g., the U.S.

As is standard in the literature using these data, the hourly wage variable is calculated as the sum of total labor market income and mandatory pension fund payments of the job held in the last week in November of a given year divided by the total number of hours worked in the job held in November of that year. The labor income and the pension contributions are from the tax authorities and are considered to be highly reliable. Wage structure is potentially affected by the presence of centralized wage bargaining in Denmark (see Dahl, le Maire, and Munch (2009) for a detailed description of the system). However, only around 13% of workers are covered by industry-wide bargaining where wages cannot be modified at the firm level. In other cases wages are bargained at the firm level, potentially subject to the lower bound on wages of the very inexperienced workers set at the industry level.

---

<sup>6</sup>For example, we find that the level of occupational mobility in Denmark is similar to the estimates of mobility in the U.S. that account for the coding error. Groes (2010) documents that the relationship between occupational tenure and wages in Denmark is similar to that found in the U.S. She also reports that the hazard rates of leaving an occupation in Denmark are similar to those estimated for the U.S.



Occupational affiliation is defined by the so-called DISCO code, which is the Danish version of the ISCO-88 classification (International Standard Classification of Occupations).<sup>7</sup> The validity of the codes is considered to be high, in particular, because they are monitored by employers and unions and form the basis of wage bargaining at the national level. We use the most disaggregated definition of the occupational classification available, i.e., the 4-digit code. This classification corresponds fairly closely to the 3-digit Standard Occupational Classification used by the U.S. Census. We perform our analysis at this level of aggregation because it appears to better match the characteristics of the tasks performed by the workers than more aggregated classifications. For example, the following pairs of occupations have distinct 4-digit codes but the same 3-digit ones: economists and foreign language translators, hair-dressers and undertakers, radio-announcers and circus clowns, plumbers and electricians, etc. Moreover, the main variable used in our analysis is the position of the worker in the wage distribution of his occupation. This is affected by the coarseness of the classification used. For example, only 28% of economists in the lowest decile of the economists' wage distribution are in the lowest decile of their 3-digit occupational group. Similarly, some workers in the lowest decile of the wage distribution of chemical engineers are in the 7<sup>th</sup> decile of the wage distribution of their 3-digit occupation. These arguments notwithstanding, however, we will show that all of the results reported below are qualitatively similar when the analysis is performed at the 1-, 2-, and 3-digit levels.

### 2.1.1 Sample Selection

While the Danish register data dates back to 1980, because information on firm tenure is available only after 1995 and because of a change in the occupational classification in 1995, we study the data spanning the 1995-2002 period (the latter cut-off was dictated by the data availability at the time we performed the analysis). We use the pre-1995 data in constructing some of the variables. For example, in 1995 the two occupational classifications used in the Danish register data are linked to the worker's job which allows us to construct measures of occupational tenure. Thus, a worker will be considered to have 5 years of occupational experience in 1996 if he is observed in the same occupation in 1995 and 1996 according to the new occupational classification and at the same time has the same occupation from 1992 to 1995 according to the old occupational classification.

For the analysis in the body of the paper, we only select male workers in order to minimize the impact of fertility decision on labor market transitions. However, for completeness, we also report a full set of results on the sample of females in Appendix OA7. The sample is restricted to

---

<sup>7</sup>The codes are described at <http://www.ilo.org/public/english/bureau/stat/isco/isco88/major.htm>, and in Appendix OA19.

employees because we do not observe earnings for the self-employed. Since we study occupational mobility between consecutive years, the sample only includes workers with valid occupation data in the year after we use them in the analysis. To construct experience and tenure variables we need to observe each individual's entire labor market history. Thus, our sample includes all individuals completing their education in or after 1980 if they remain in the sample at least until 1995. The sample includes graduates from all types of education from 7th grade to a graduate degree conditional on observing the individual not going back to school for at least three years after graduation. Thus, a worker who completed high school, worked for three years, then obtained a college degree and went back to full-time work will have two spells in our sample: first, the three years between high school and college, and second, after graduating from college. If he worked for less than three years between high school and college, he joins our sample only after graduating from college.

We conduct our analysis using two samples that differ in additional restrictions that we impose. We label these samples a *Small Sample* and a *Large Sample*. Their construction is as follows.

Our overriding concern in constructing the Small Sample is the reliability and consistency of the data. This sample is restricted to full time workers in the private sector. The restriction to private-sector workers is due to the concern that wage setting and mobility patterns in the government sector may be partially affected by non-market considerations. Part-time workers are excluded because they do not have as dependable wage information and the majority do not have any occupational codes. We truncate workers' labor market histories the first time we observe them in part-time employment, public employment, self-employment, or at the first observation with missing wage data or missing firm or occupational codes.<sup>8</sup> In order to have the same distribution of experience in the period 1995 to 2002 we truncate worker histories 15 years after graduation.

Our main objective in constructing the Large Sample is to maximize the size of the sample. Consequently, it is much less restrictive. It includes public-sector workers and includes workers who have spells of part-time work and non-employment.<sup>9</sup> It also includes workers who re-enter the sample after having a missing firm, industry, or occupational spell.<sup>10</sup>

---

<sup>8</sup>Workers are allowed to be either unemployed or out of the labor force up to two years after graduation without being dropped from the sample.

<sup>9</sup>We treat part time work as non-employment.

<sup>10</sup>We exclude observations with missing occupational or firm affiliation data. After an observation with missing occupation (firm) affiliation we cannot reliably calculate occupational (firm) tenure until the worker is observed switching occupations (firms). Upon an occupational (firm) switch the corresponding tenure is set to zero and from that point on the observations are included into the sample. For example, a worker who is a cook in period  $t$ , has missing occupation in period  $t + 1$ , is a cook in period  $t + 2$ , and a truck driver in period  $t + 3$ , will be

Descriptive statistics of the main samples used in the analysis are provided in Appendix Table A-1. The results reported in the body of the paper are mainly based on the Small Sample that contains approximately 450,000 observations.

The results based on the Large Sample that includes approximately 1.3 million observations are reported in Appendix OA4. They have the same qualitative features as the results based on the Small Sample. We have also verified that all the results hold for the “intermediate” samples that impose some but not all of the restrictions of the Small Sample.

## 2.2 U-shapes in the Probability of Occupational Switching

In this section we present evidence of U-shapes in the probability of occupational switching. For each worker that we observe in a given year of our sample, we compare his wage to the wages of the other workers *in the same occupation* in the same year. This gives us this worker’s rank in the wage distribution of his occupation. That is, it gives the fraction of other workers in the same occupation that earn lower wages than him this year. We plot the probability of switching to a new occupation in the following year against this rank. Figure 1(a) is a non-parametric plot (from a kernel smoothed local linear regression with bandwidth of 5 percentiles) of the probability of switching out of an occupation as a function of a worker’s position in the wage distribution in that occupation in a given year.<sup>11</sup> The probability of switching occupation is clearly U-shaped in wages. It is the workers with the highest or lowest wages in their occupations who have the highest probability of leaving the occupation. The workers in the middle of the wage distribution of their occupation have the lowest probability of switching occupations.

Figure 1(a) is based on raw wage data. Figure 1(b) indicates that we also observe a U-shaped pattern of occupational mobility in the position of the worker in the distribution of residual wages in his occupation in a given year. We generate residual wages by estimating a standard reduced-form wage regression

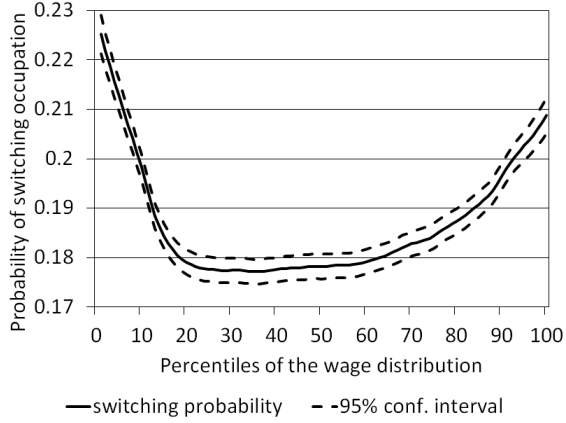
$$\ln w_{ijt} = X_{ijt}\beta + \epsilon_{ijt}, \quad (1)$$

where  $w_{ijt}$  is real hourly wage of an individual  $i$  working in occupation  $j$  in period  $t$  and  $\epsilon_{ijt}$  is the residual. The explanatory variables in  $X$  include calendar year dummies, third degree polynomials in general experience, occupational tenure, industry tenure, a second degree polynomial in firm tenure, the sequence number of occupational spell, education, marital status, union membership, and lagged regional unemployment rates. These wage regressions are estimated separately for

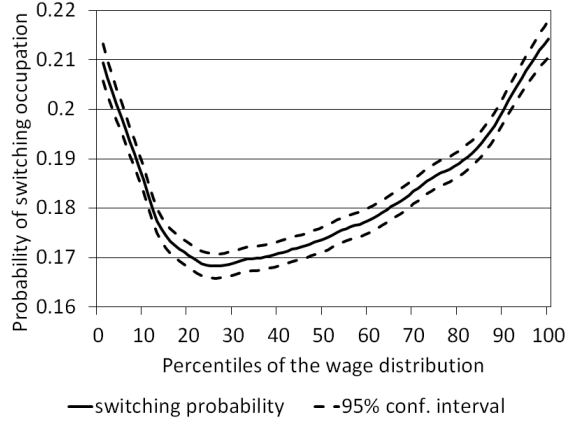
---

included in the sample in period  $t$  and again in period  $t + 3$  – the two observations with reliable occupational tenure information.

<sup>11</sup>The occupations are restricted to include a minimum of ten workers per year in order to find the percentiles of the wage distribution within an occupation.



(a) Distribution of raw wages within occupation and year.



(b) Distribution of wage residuals.

Figure 1: Non-parametric plot of probability of switching occupation by worker's percentile in the relevant wage distribution.

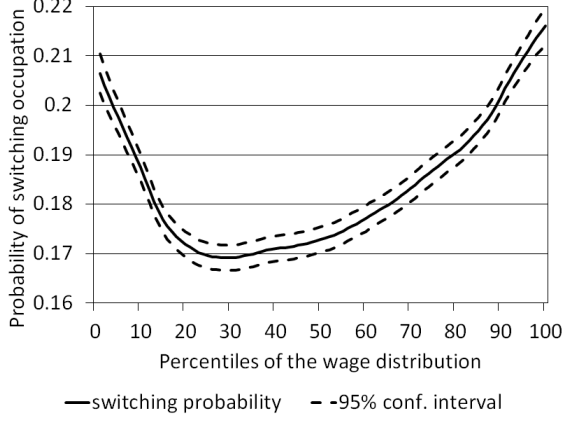
each occupation.<sup>12</sup>

The U-shaped pattern of mobility is also evident in Figure 2(a) where we plot the probability of switching out of an occupation against worker's rank in the distribution of wages within occupation, year, and among workers with the same number of years after graduation. That is, we compute the rank of the individual in the distribution of wages of workers who completed their education in the same year and work in the same occupation in a given year. Figure 2(b) separately graphs occupational mobility for workers who graduated 1, 2, 4, and 6 years ago. While the rate of occupational mobility generally declines with labor market experience, the U-shaped pattern of occupational mobility is pronounced for all years after graduation.<sup>13</sup>

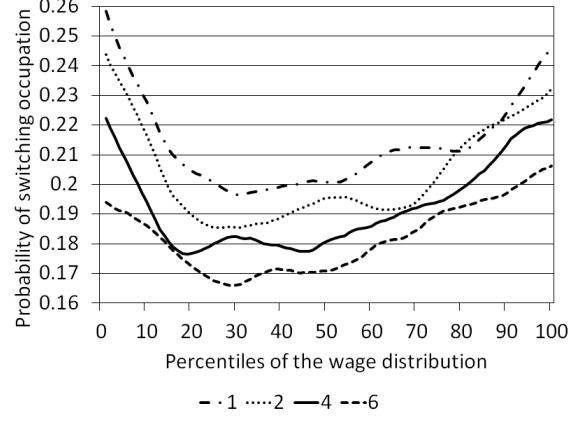
To assess the prevalence of U-shaped pattern of occupational mobility we compute the fraction of occupations featuring U-shapes and the fraction of workers employed in these occupations. Computing these statistics requires enough workers in each occupation in each year to accurately predict the probability of changing occupation in different parts of the wage distribution of that occupation. Thus, we restrict the sample to occupations that include at least 100 workers in a given year. Separately for each occupation, we estimate the probit regression of the probability of switching occupation on a  $2^{nd}$  degree polynomial in worker's percentile in the wage

<sup>12</sup>Appendix Figure OA-1 shows that excluding firm and industry tenure or dummies for the sequence number of the occupational spell from the wage regression does not qualitatively affect the results. Appendix Figures OA-2 to OA-4 illustrate that the U-shaped pattern of mobility is robust to alternative bandwidths choices.

<sup>13</sup>Because tenure predicts mobility (inversely), labor market transitions tend to be correlated over time for the same individual. Workers who just switched are at the highest risk of switching again. Therefore, annual data like IDA, which miss multiple intra-annual transitions, are likely to dampen U-shapes, as they count any number of transitions as if they were one.



(a) Overall.



(b) For different years after graduation.

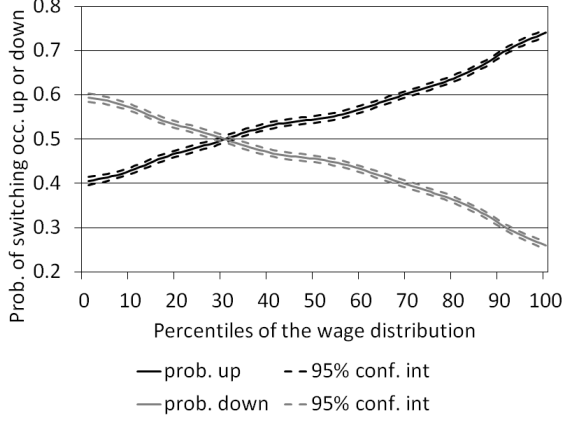
Figure 2: Non-parametric plot of probability of switching occupation by worker's percentile in the distribution of raw wages within occupation, year, and years after graduation.

distribution within occupation and year, i.e.  $Pr(\text{switch}) = \Phi[\alpha + \beta \cdot \text{perc} + \gamma \cdot \text{perc}^2]$ . The partial effect of the wage percentile on the probability of switching occupation is  $\frac{\partial Pr(\text{switch})}{\partial \text{perc}} = \phi(\alpha + \beta \cdot \text{perc} + \gamma \cdot \text{perc}^2)(\beta + 2\gamma \cdot \text{perc})$ . The U-shaped pattern implies that this derivative evaluated at  $\text{perc} = 0$  must be negative, that is  $\phi(\alpha)(\beta) < 0$ . Similarly, the U-shaped pattern also implies that the derivative evaluated at  $\text{perc} = 1$  must be positive, i.e.,  $\phi(\alpha + \beta + \gamma)(\beta + 2\gamma) > 0$ . In our Small Sample, 66% of occupations (employing 83% of workers) satisfy both of these criteria when percentiles are defined in raw wages. If percentiles are defined in wage residuals, 74% of occupations (employing 85% of workers) satisfy these criteria. In our Large Sample, 75% of occupations (employing 86% of workers) satisfy both of these criteria when percentiles are defined in raw wages. If percentiles are defined in wage residuals, 82% of occupations (employing 92% of workers) satisfy these criteria.<sup>14</sup>

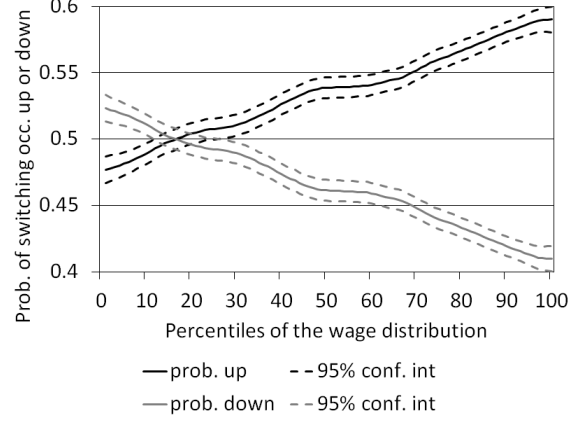
### 2.3 U-shapes in the Direction of Occupational Switching

In this section we document another prominent feature of the data: conditional on changing occupation, workers with higher (lower) relative wages *within* their occupation tend to switch to occupations with higher (lower) *average* wages than the average wage in their current occupation. We first find the average wage of all occupations in a given year in order to determine the ranking between occupations. Similarly to our analysis of probability of occupational switching, we rank

<sup>14</sup>For the reasons that would become apparent in Section 4, U-shaped pattern of occupational mobility is considerably more prevalent among occupations that do not experience large changes in relative productivity. For example, restricting attention to occupations in the interior 80% of wage growth, 85% of occupations (employing 91% of workers) satisfy both of these criteria when percentiles are defined in raw wages. If percentiles are defined in wage residuals, 92% of occupations (employing 95% of workers) satisfy these criteria.



(a) Distribution of raw wages within occupation and year. Average wage in occupation from population.



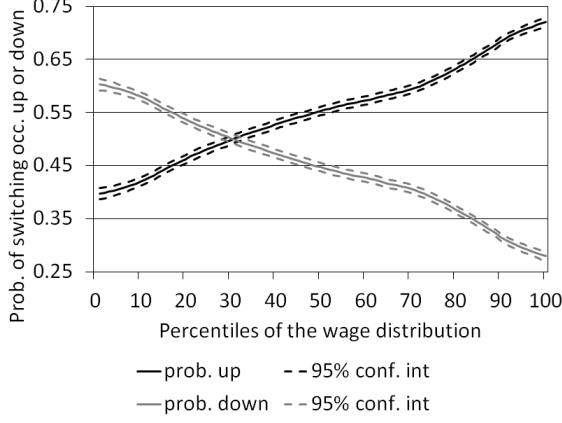
(b) Distribution of wage residuals. Average wage in occupation from time constants in wage regression.

Figure 3: Non-parametric plot of direction of occupational mobility, conditional on switching occupation, by worker's percentile in the relevant wage distribution before the switch.

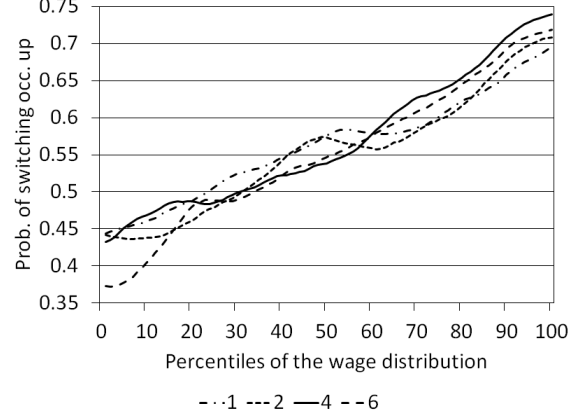
occupations based on their raw wages or residual wages adjusted for worker characteristics. To obtain the ranking based on raw wages, we find the average real wage of all full-time private-sector workers in a given occupation in a given year.<sup>15</sup> To obtain the ranking based on residual wages, we use our selected sample to run a similar wage regression as in Equation 1 for each occupation where we include time dummies in the regression (without the intercept). We interpret the coefficients on these time dummies as the average occupational wage in a given year, adjusted for human capital accumulation of workers in the occupation as well as other worker characteristics such as education, regional dummies, and marital status.

Figure 3(a) plots the probability of switching to an occupation with a higher or lower average wage as a function of the worker's position in the wage distribution of the occupation he or she is leaving. The sample on which the figure is based consists of all workers who switched occupation in a given year and occupations are ranked based on the raw average wages. Figure 3(b) presents corresponding evidence when occupations are ranked based on residual wages and the direction of occupational mobility is plotted against the percentile in the distribution of residual wages within an occupation the worker is switching from. The evidence contained in these figures suggests that, conditional on switching occupations, the higher relative wage a person has in his occupation before the switch, the higher is the probability that he will switch to an occupation with a higher average wage. Similarly, the lower relative wage a worker has in his occupation before the switch, the higher is the probability that he will switch to an occupation with a lower

<sup>15</sup>Note that this is a bigger sample than our selected sample. The results are, however, robust to only looking at the average wages in our selected sample.



(a) Overall.



(b) For different years after graduation.

Figure 4: Non-parametric plot of direction of occupational mobility, conditional on switching occupation, by worker's percentile in the distribution of raw wages within occupation, year, and years after graduation before the switch.

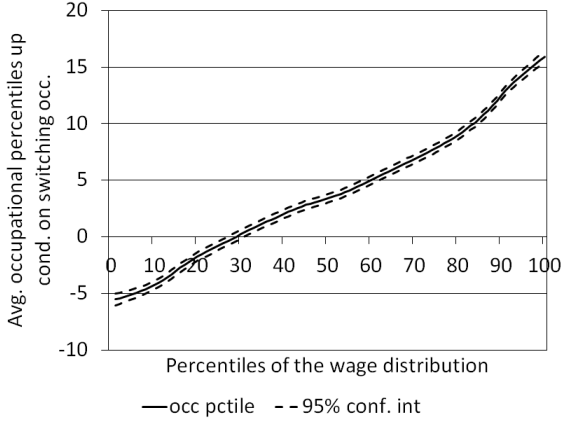
average wage than in the occupation he switches from.

Figure 4(a) illustrates that similar results hold if we further condition on worker's position in the distribution of wages in his occupation in a given year and among people with the same number of years since graduation. This figure is comparable to Figure 3(a) in that occupational average wages are calculated from raw wages of the population in the occupation in a given year. Finally, Figure 4(b) shows that the direction of occupational mobility is similar for individuals who graduated 1, 2, 4, or 6 years prior.

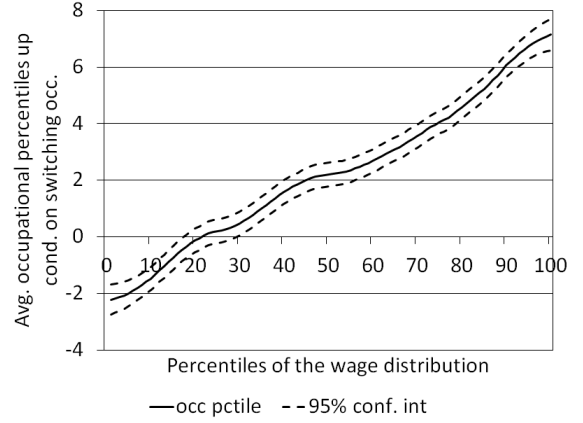
## 2.4 Discussion of Empirical Evidence

### 2.4.1 Magnitudes of Changes in Occupational Ranks

In Figure 5 we describe, for occupational switchers, the relationship between the worker's rank in the wage distribution of his occupation and the change in the rank of the occupational average wage upon a switch (construction of the latter was described in Section 2.3). The Figure indicates that workers above the 30th wage percentile of the wage distribution within their occupation tend to move to occupations with higher average wages than the occupation they came from, while workers below the 30th percentile on average move to lower ranking occupations. This point roughly corresponds to the crossing of the two lines in Figure 3.



(a) Distribution of raw wages within occupation and year.



(b) Distribution of wage residuals.

Figure 5: Non-parametric plot of direction of occupational mobility in terms of change of occupational percentiles, conditional on switching occupation, by worker's percentile in the relevant wage distribution.

#### 2.4.2 U-shapes of Occupational Mobility within and between Firms

Our findings remain robust if we separately consider occupational switchers who stay with their firms and occupational switchers who change firms as well.<sup>16</sup> In both samples the probability of switching remains U-shaped in the position of the worker in the wage distribution of his occupation. Moreover, in both samples mobility is directional so that the relatively high (low) wage workers in their occupation tend to switch to occupations that pay on average higher (lower) wages. While the average probability of switching occupations is higher among those who switch firms than among those who stay with the same firm, possibly because occupational switching often necessitates switching firm if the new occupation is not represented in the old firm, the directional switching probabilities are virtually indistinguishable between the two samples. Figures 6 and 7 summarize this evidence when the worker's relative position in the wage distribution is determined based on raw wages. Appendix Figures OA-12 and OA-13 summarize this evidence when the worker's relative position in the wage distribution is determined based on wages residuals.<sup>17</sup> After developing our theory of occupational mobility, we combine it with a simple theory of firm mobility in Appendix OA14.4 and show that the combined theory is quantitatively capable

<sup>16</sup>It does not appear possible to distinguish voluntary from involuntary occupational changes. Thus the terminology "occupation change" might be more accurate than occupation "switching," especially for workers who change firm as we do not know whether the change was initiated by the worker.

<sup>17</sup>We use the worker's position in the overall wage distribution to plot these figures (i.e., the same distribution on which our unconditional on firm switching findings were based). An alternative is to define worker position in the wage distribution of the subsample he belongs to (i.e., firm switchers or firm stayers) and plot the probability of switching and the direction of switching against this rank. Qualitatively, this does not affect our findings.



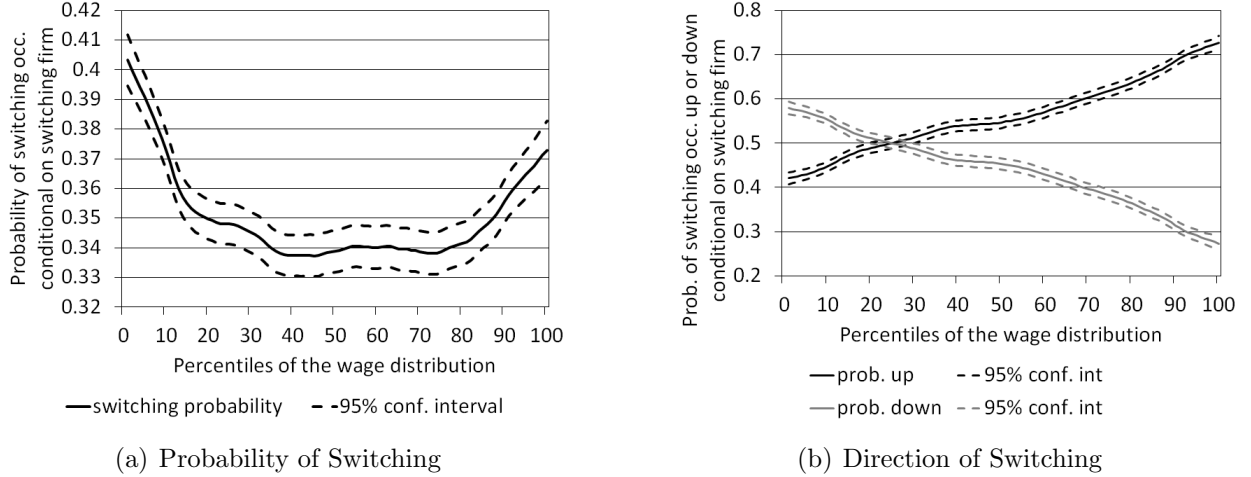


Figure 6: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on switching firms* by worker's percentile in the distribution or raw wages.

of accounting for the differences in the U-shapes of occupational mobility conditional on staying with or switching firms in Figures 6 and 7.

These results suggest that unemployment is not the main driver of the occupational switching. As Appendix Table A-2 indicates, there is sizable rate of occupational mobility within firms in Denmark, and this mobility exhibits similar patterns as those for the entire population of workers. High occupational mobility within firm has also been documented for the U.S. by Kambourov and Manovskii (2008). Moreover, a non-trivial fraction of workers who stay with the same firm switch to occupations that on average pay less to their workers.

This raises the question whether switches to lower-ranked occupations within a firm are indeed associated with lower wage growth for the individual worker, or whether they are just labels that are inconsequential for the actual wage and position that the individual workers has within the firm. Table A-2 contains evidence that the consequences for workers' wage growth are substantial both for workers that stay within the same firm as well as for those that switch firms. Among workers who stay with their firm, those who move to higher-ranked occupations see significantly higher wage growth than those who stay in the same occupation. Those workers who move to lower-ranked occupations see a significantly lower wage growth than those who stay in the same occupation. These wage changes persist five years after the occupational transition.<sup>18</sup> These patterns are similar for workers switching firms although the wage changes for this group

<sup>18</sup>To construct five-year wage changes we restrict the sample to workers who remain in their occupations or switch to higher/lower ranked occupations in 1995, 1996, and 1997 and for who we can observe wages five years later in 2000, 2001, and 2002.

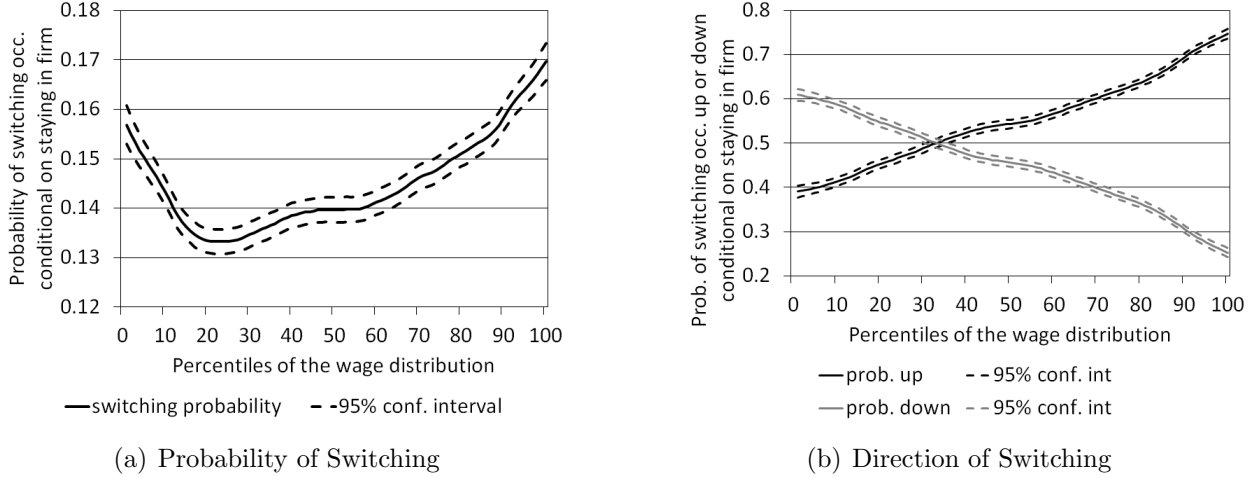


Figure 7: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on staying with the firm* by worker's percentile in the distribution of raw wages.

of workers are somewhat larger.

#### 2.4.3 The U-shapes of Occupational Mobility: Females

While our main analysis focuses on the sample of male workers to avoid possible impact of fertility decisions on labor market transitions, in Appendix OA7 we provide a complete set of results on the U-shapes of mobility on the sample of females. The sample is constructed by imposing exactly the same restrictions as on the sample of males. To avoid cluttering the paper, we report the results for females only on the Large Sample, but note that all the results are fully robust to using the Small Sample as well.

We find that the results on the female sample parallel the results documented above on the sample of males. In particular, the probability of an occupational switch is U-shaped in the position of a female worker in the distribution of wages (either raw or residual) in her occupation. Interestingly, the U-shape is somewhat skewed to the right, so that women who are particularly successful in their occupations are even more likely to switch than the particularly unsuccessful ones, who, by the definition of the U-shape, are more likely to switch than the women in the middle of the occupational wage distribution. Occupational mobility on the sample of females is also directional. Relatively more successful women in an occupation tend to switch to higher ranked occupations, while relatively less successful women are more likely to switch to lower ranked occupations. The magnitudes of the jumps in occupational ranks conditional on occupational change are also similar in the samples of women and men. Finally, the U-shaped patterns of

occupational mobility remain robust to conditioning on switching employers or remaining with the current one.

#### 2.4.4 Alternative Occupational Classifications

In interests of space, we explore the sensitivity of our findings to alternative definitions of occupations in Appendix OA8. In particular, we consider (1) 1-, 2-, and 3-digit occupational classifications as opposed to the 4-digit classification used in our main analysis, (2) mobility across occupational groups within which workers perform relatively similar tasks, (3) classifying all managers as one occupation or excluding them from the sample altogether, (4) excluding the “... not elsewhere classified” occupations from the analysis.<sup>19</sup> In all these experiments we find that while the level of mobility is affected by the change in occupational classifications, the U-shaped pattern of mobility remains unchanged.

#### 2.4.5 The Effects of Measurement Error

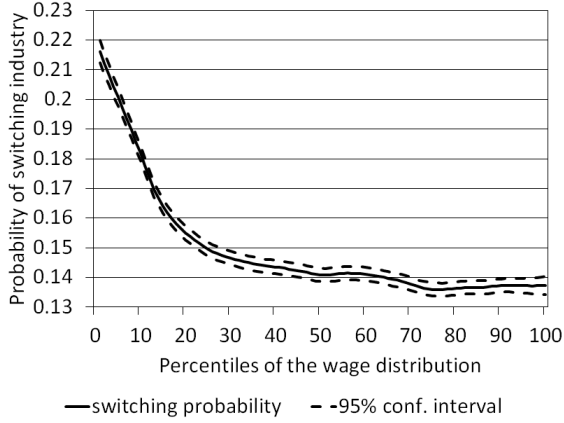
While the occupational affiliation data we use is generally regarded to be highly reliable, some coding error might be present. To investigate the potential effect of the measurement error on our findings we document the patterns of mobility for workers whose occupational affiliation is stable over several time periods and therefore less prone to possible temporary coding errors. When considering whether a worker switches occupation between periods  $t$  and  $t + 1$  we now only consider workers who have been in the same occupation for at least the two years  $t - 1$  and  $t$  and then stay in the same occupation for at least the two years  $t + 1$  and  $t + 2$ . We also consider workers with at least three years of occupational affiliation before and after the potential switching point. The shape and direction of mobility for these workers is reported in Figures OA-14 through OA-17 in Appendix OA6. We find that our results remain robust. Similar results are obtained on the samples of occupational switchers within and across firms. We discuss additional evidence on the role of measurement error in Appendix OA9.

#### 2.4.6 Focus on Occupational Mobility

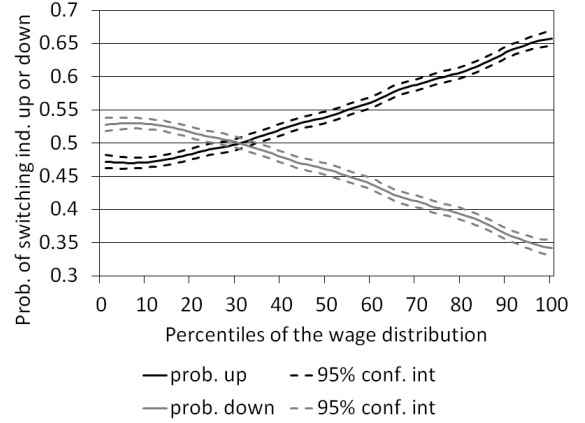
Our primary focus is on worker mobility across occupations which were shown in prior work to be major predictors of individual earnings. We have repeated the analysis on industries and found that mobility across industries does not exhibit U-shapes. Instead, Figure 8(a) illustrates that it

---

<sup>19</sup>In addition to helping assess whether our finding that workers with relatively high wages are more likely to leave their occupations is predominantly driven by promotions to managerial occupations, the latter experiments are relevant to the contention of Mouw and Kalleberg (2010) that in U.S. data the polarization of occupations is due to a relatively small number of occupations, of which “Managers and Administrators, Not Elsewhere Classified” is an important one.



(a) Probability of switching industry



(b) Direction of industry mobility

Figure 8: Non-parametric plots of probability of switching industry and of direction of industry mobility conditional on switching industry, by worker's percentile in the distribution of raw wages within industry and year.

is poor matches in the bottom part of the wage distribution in an industry that are more likely to be destroyed. These patterns are similar to those documented in the US data by Bils and McLaughlin (2001) who found that at cyclical frequencies industry switchers come from the lower part of the wage distribution in the industry they leave.<sup>20</sup>

In Figure 8(b) we plot the direction of industry mobility. The results indicate that, conditional on switching industries, workers are much more likely to move into industries that on average pay more to their workers. There is however a weaker relationship (as compared to Figure 3(a) for occupations) between the relative position of the worker in the wage distribution in his industry and the rank of the industry he is switching to.

The difference between occupation and industry switching might be due to the fact (also pointed out by Bils and McLaughlin (2001)) that industries have less of a natural ladder. Workers who find out that they are very talented may not change industries, but are likely to switch to more demanding occupations, explaining the flat right-hand side of Figure 8(a). Similarly, if workers move up to better occupations within their industry, the move across industries might be driven by other considerations.<sup>21</sup>

It is also very interesting to assess the extent and patterns of sorting across firms. Unfortu-

<sup>20</sup>Similar to those authors, we also find that industry switchers tend to enter in the bottom of the wage distribution in the destination industries.

<sup>21</sup>One interpretation is that some industries are paying more than other across all levels of worker skills, and therefore independently of the current ability all workers queue for jobs in the higher-paying industries. Such a queuing theory would explain why workers across the wage-spectrum move to higher-paying industries over time. In contrast, better occupations might only pay more to very high-qualified applicants, and only those at the top within a given occupation might qualify, which is the view that we will formalize below in the theory section.

nately we cannot apply our methodology at the firm level because firms in Denmark are generally too small for this purpose, especially since one would presumably need to condition on workers' occupation.

### 2.4.7 Summary

To summarize the evidence presented so far, the probability of switching out of most occupations is U-shaped in the position of the worker in the wage distribution of that occupation. Workers with high wages relative to their occupational average tend to switch to occupations with higher average wages. Workers with low wages relative to their occupational average tend to switch to occupations with lower average wages.

The fact that high paid workers tend to switch to occupations that on average pay more suggests a model in which absolute advantage (high pay) goes hand in hand with comparative advantage in the more productive occupations (switching to better occupations). This is called positive sorting in traditional Roy models, and will be a central element of the following theory. We confront additional implications of the theory with the data as we derive them.

## 3 The U-shapes of Occupational Mobility: Theory

In this section we present a model of vertical sorting, where gross mobility arises since workers initially have only limited information about their ability and learn about it over time. In the model it is efficient that workers of higher ability work in the occupations where ability is most valued. If a worker learns that he is much better (or worse) than expected, he adjusts (has to adjust) to an occupation commensurate with his ability.

We show that the combination of learning and sorting is sufficient to generate the qualitative patterns that we find in the data. To highlight the basic impact of these two features, we abstract from other factors such as human capital accumulation and costs of occupational switching. We discuss in the Appendix how these features can be integrated. They do not offset the qualitative implications of sorting, but we discuss them because we expect them to be important for any quantitative assessment of the theory. Finally, we consider the validity of some secondary implications of the theory.

### 3.1 The Model

*Workers:* Workers choose employment in different occupations over time. Time is discrete and runs forever. Each period a unit measure of workers enters the labor market. The index for an

individual worker will be  $i$  throughout. Each worker is in the labor force for  $T$  periods. Workers are risk-neutral and discount the future with a common discount factor  $\beta$ . Each worker has an innate ability level  $a_i$  that is drawn at the beginning of his life from a normal distribution with mean  $\mu_a$  and variance  $\sigma_a^2$ . For the baseline model without human capital accumulation we assume that this ability remains constant throughout a worker's life (we relax this in Section 4). The amount of output that a worker can produce depends on his ability. In particular, he produces

$$X_{i,t} = a_i + \varepsilon_{i,t} \quad (2)$$

in a given period  $t$  of his life, where  $\varepsilon_{i,t}$  is a normally distributed noise term with mean zero and variance  $\sigma_\varepsilon^2$ . Workers do not know their ability (and neither do firms), but workers observe the output they produce. We assume that the worker observes an initial draw after finishing school, i.e., before entering the labor market.<sup>22</sup>

Over time, workers learn about their true ability. Let  $\phi_a = 1/\sigma_a^2$  and  $\phi_\varepsilon = 1/\sigma_\varepsilon^2$  denote the precision for each distribution, which is defined as the inverse of the variance. Define the cumulative precision of a worker at the beginning of his  $t^{\text{th}}$  year in the labor market as  $\phi_t := \phi_a + t\phi_\varepsilon$ .<sup>23</sup> Initially every worker only knows that his ability is distributed with mean  $A_0 = \mu_0$  and precision  $\phi_0 = \phi_a$ . Standard results on updating of normal distributions establish that his belief at the beginning of every period  $t > 0$  of his life is normally distributed with mean  $A_{i,t}$  and precision  $\phi_t$ , where the mean is determined successively by the output realizations that he observes. After observing some output realization  $X_{i,t}$  the new mean is given by the precision-weighted average of the prior mean and the output observation:

$$A_{i,t+1} = \frac{\phi_t}{\phi_{t+1}} A_{i,t} + \frac{\phi_\varepsilon}{\phi_{t+1}} X_{i,t}. \quad (3)$$

From the point of view of the individual, this evolution of the posterior is a martingale with decreasing variance: The weight on the prior increases the more observations have already been observed in the past, i.e., the higher is  $t$  (see, e.g., Chamley (2004)). Correspondingly, the weight on the most recent observation decreases with years in the labor market. For all practical purposes, (3) can be interpreted as some exogenous change in workers ability, even though the learning interpretation appears to be particularly natural. In the following we will refer to  $A_{i,t+1}$  as the expected ability or simply as the belief, and drop the person-identifier  $i$  and/or the time identifier  $t$  when there is no danger of confusion.

---

<sup>22</sup>In general we allow this error term to be distributed with a different variance  $\sigma_0^2$  that might not coincide with the variance of the labor market error term  $\sigma_\varepsilon^2$ . While our exposition is presented for  $\sigma_0^2 = \sigma_\varepsilon^2$ , the more general expressions can be obtained with minor modifications mentioned below.

<sup>23</sup> If the first ability signal before the worker enters the labor market has variance  $\sigma_0^2 \neq \sigma_\varepsilon^2$ , this can be accommodated by adjusting the cumulative precision to  $\phi_t = \phi_a + \phi_0 + (t-1)\phi_\varepsilon$ , where  $\phi_0 = 1/\sigma_0^2$ .

For completeness, we define the following two distributions. First, let  $G_t(A_{t+1}|A_t)$  denote the distribution of next period's belief for a worker with current belief  $A_t$ . It is normal with mean  $A_t$ .<sup>24</sup> In particular, its density  $g_t$  is single-peaked and symmetric around its peak at  $A_t$ , and shifting the prior mean  $A_t$  simply shifts the entire distribution about the posterior horizontally in the sense that  $g_t(A_{t+1}|A_t) = g_t(A_{t+1} + \delta|A_t + \delta)$  for any  $\delta$ . This is all we need for most proofs.<sup>25</sup> We call the latter property *lateral adjustment*. Second, the cross-sectional distribution  $F_t(A)$  of beliefs among workers that start the  $t^{\text{th}}$  period of their working life can be computed from (3) and is independent of any choices that agents make.<sup>26</sup> Therefore, the measure of agents with belief below  $A$  across all cohorts at any point in time,  $F(A) = \sum_{t=1}^T F_t(A)$ , can be computed prior to any analysis of occupational choice. This simplifies the specification of an equilibrium.

*Occupations:* There are a finite number of occupations, indexed by  $k \in \{0, 1, \dots, K\}$ , each with some fixed measure  $\gamma_k$  of available jobs. We treat the number of jobs as exogenous in this exposition, yet Appendix OA16 discusses how endogenous entry can be accommodated (limited entry and associated competition among workers for scarce jobs will be most important in Section 4 to explain the mobility patterns when occupational productivities change).

Each unit of the good (or service) that is produced sells in the market at some exogenously given price  $P_k$ . Therefore, worker  $i$  employed in a job of type  $k$  generates revenue

$$R_{ki} = P_k X_i. \quad (4)$$

Equivalently, we can interpret  $P_k$  as the productivity in terms of efficiency units of the labor (at a common sale price of unity). We rank occupations in order of increasing productivity such that  $P_K > \dots > P_k > \dots > P_0 = 0$ . Therefore, any given worker produces more in a higher ranked occupation. One can view the lowest ranked occupation as home production. An output signal is observable even in home production, and home production is available to everybody (more jobs than population size:  $\gamma_0 \geq T$ ). All other jobs are assumed to be scarce (less jobs than workers

---

<sup>24</sup>Conditional on knowing the true ability  $a$  of a worker, the output  $X_t$  is distributed normally with mean  $a$  and precision  $\phi_\epsilon$ , i.e.  $X_t \sim N(a, \phi_\epsilon)$ . Yet the ability is not known. Rather, the individual only knows his expected ability  $A_t$  while his true ability is a draw  $a \sim N(A_t, \phi_t)$ . Integrating out the uncertainty over his ability implies that output is distributed  $X \sim N(A_t, \phi_\epsilon \phi_t / \phi_{t+1})$ . We are not interested in the output per se, but in the update  $A_{t+1} = (\phi_\epsilon X_t + \phi_t A_t) / \phi_{t+1}$  as a function of output. This linear combination implies that the posterior distribution  $G_t(A_{t+1}|A_t)$  is a normal with mean  $A_t$  and precision  $\phi_t \phi_{t+1} / \phi_\epsilon$ , i.e.  $A_t \sim N(A_t, \phi_t \phi_{t+1} / \phi_\epsilon)$ .

<sup>25</sup>For one proof (Proposition 4) we also need concavity of  $g_t(A_{t+1}|A_t)$  in  $A_{t+1}$  locally for  $A_{t+1}$  near  $A_t$ , which holds for the normal distribution.

<sup>26</sup>At the beginning of period  $t$  the workers have observed  $t$  output observations (one in school and  $t - 1$  in the labor force). The only relevant information for the worker is the average  $\bar{X}$  of these output realizations. Conditional on  $a$  this is distributed normally with mean  $a$  and precision  $t\phi_\epsilon$ . Since  $a$  is not known, an agent with prior  $\mu_a$  faces realizations of  $\bar{X}$  that are normal with mean  $\mu_a$  and precision  $t\phi_\epsilon \phi_a / \phi_t$ . Since the update is  $A^t = (t\phi_\epsilon \bar{X} + \phi_a \mu_a) / \phi_t$ ,  $F^t$  is normal mean  $\mu_a$  and precision  $\phi_t \phi_a / (t\phi_\epsilon)$ .

with positive ability:  $\sum_{k=1}^K \gamma_k < T - F(0)$ .<sup>27</sup>

*Wages:* We consider a competitive economy without matching frictions. The only frictions are information frictions in the sense that workers' actual abilities are not known. There are (at least) two ways to think about wage-setting in our economy. Wages might be output-contingent contracts  $w(X)$  that specify different wages based on the particular output that is realized. If a firm wants to obtain profits  $\Pi_k$  it can simply offer the wage contract

$$w_k(X) = P_k X - \Pi_k \quad (5)$$

to any worker who is willing to take this contract. Since workers are risk-neutral, they choose the occupation with the highest expected wage. Therefore, it is not necessary that the firm has as much information as the workers, since workers would self-select. The relevant sorting criterion for risk-neutral workers is their expected wage given their belief  $A$  about their mean ability:

$$W_k(A) = P_k A - \Pi_k. \quad (6)$$

Alternatively, if the firm has the same information as the worker it can directly pay expected wages according to (6). In this case the firm absorbs all the risk. It would need to have the same information as the worker because otherwise it might attract workers with low expected abilities who try to get a high pay. Given risk-neutrality, whether firms or workers face the output risk does not affect the occupational choices by workers because in either case workers only care about expected wages (given by (6)), but observed wages differ according to the specification and could potentially lead to different assessments of observed wage patterns. We will show our main qualitative results under both wage setting regimes. In fact, firms might pay workers according to some weighted average of (5) and (6) to provide both incentives for self-selection as well as insurance to workers, and our arguments can easily be extended to show that our main propositions hold for any such convex combination.

*Equilibrium:* We are considering a standard stationary competitive equilibrium in this matching market between occupations and workers. As market prices one can use either profits or wages, as one determines the other via (5) [or (6)]. It is notationally more convenient to focus on the profits. Stationary means that the entrepreneurs' profits  $\Pi = (\Pi_1, \Pi_2, \dots, \Pi_K)$  and the associated wage offers are constant over time. The tractability of the baseline model arises from the fact that every period workers can costlessly re-optimize and therefore the sequence of decisions that maximize their life-time income coincides to the sequence of decisions that maximizes their payoff

---

<sup>27</sup>Otherwise the lowest occupations would not attract any workers and would simply not be observed in the data.



in each period. Since the cross-sectional distribution of beliefs  $F(A)$  remains constant, we can use standard tools for the analysis of static matching models. In particular, a worker will work in occupation  $k$  rather than  $k - 1$  if the expected wage is higher:  $P_k A - \Pi_k \geq P_{k-1} A - \Pi_{k-1}$ . There is exactly one level of expected ability, call it  $B_k$ , at which this holds at equality:

$$B_k \equiv \frac{\Pi_k - \Pi_{k-1}}{P_k - P_{k-1}}, \text{ for } k \in \{1, \dots, K\}. \quad (7)$$

Therefore, workers optimally choose to work in occupation  $k$  if their expected ability is within the interval  $[B_k, B_{k+1})$ , where we define  $B_0 \equiv -\infty$  and  $B_{K+1} \equiv \infty$ .<sup>28</sup> Market clearing then means that the number of workers  $F(B_{k+1}) - F(B_k)$  that would like to work in occupation  $k$  coincides with the number of jobs  $\gamma_k$  available in this occupation:

$$\gamma_k = F(B_{k+1}) - F(B_k), \text{ for } k \in \{1, \dots, K\}. \quad (8)$$

The system (7) and (8) can easily be solved recursively: Summing (8) across all  $k$  and noting that  $F(B_{K+1})$  equals the total population  $T$ , we get  $\sum_{k \in \{1, \dots, K\}} \gamma_k = T - F(B_1)$  which determines  $B_1$ . Then successive application of (8) yields the remaining cutoff levels  $(B_2, \dots, B_K)$ . Since zero productivity in the lowest occupation implies zero profit, (7) then delivers the profits of the firms in the various occupations  $(\Pi_1, \dots, \Pi_K)$ . To sum up:

**Definition 1** *An equilibrium is a vector of profits  $\Pi = (\Pi_0, \dots, \Pi_K)$  with  $\Pi_0 = 0$  and a vector of optimal worker cutoff level  $(B_1, B_2, \dots, B_K)$  such that equations (7) and (8) hold.*

### 3.2 Analysis: Shape and Direction of Occupational Mobility

Consider a worker who chooses occupation  $k$  in his  $t^{\text{th}}$  year of labor market experience, and earns wage  $W$  as in (6). Let  $S_{k,t}(W)$  be the probability that this worker switches, i.e., that he chooses a different occupation in  $t + 1$ . We will use the superscript "+" to indicate the probability of switching to a higher occupation, and "-" to indicate the probability of switching to a lower occupation. Clearly  $S_{k,t}(W) = S_{k,t}^+(W) + S_{k,t}^-(W)$ . Similarly, if wages are set by (5), then denote the wage by lower-case letter  $w$  and the corresponding switching probabilities by  $s_{k,t}(w)$ ,  $s_{k,t}^+(w)$  and  $s_{k,t}^-(w)$ . To analyze these switching probabilities formally, we adopt the following definition.

---

<sup>28</sup>This sorting property is driven by the fact that our expected revenue function is supermodular, as highlighted in the seminal contribution by Becker (1973). Nevertheless, there are revenue functions different from the one that we assume that give rise to exactly the same wage patterns despite the fact that more able workers work in less productive occupations (this arises for example when revenues are  $R_{ki} = P_k + (1 - P_k)X_i$ , see Eeckhout and Kircher (2011) for details). In general, what is important for our results is that there is some benefit from sorting into the appropriate occupation given one's skills, so that workers adjust their occupation as they learn their type more precisely.

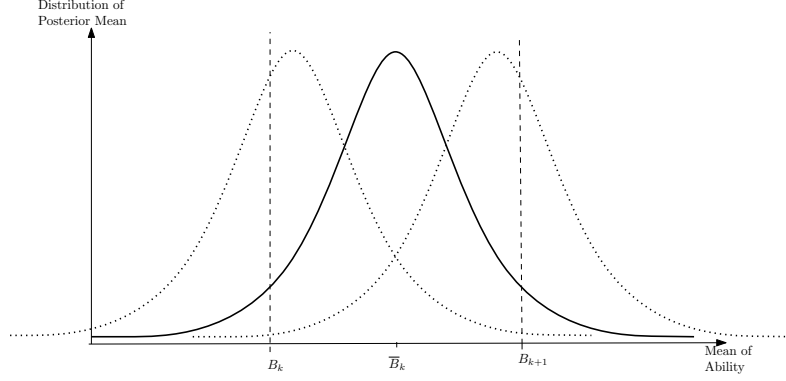


Figure 9: Illustration of the proof of Propositions 1 and 2.

**Definition 2 (U-shapes)** *A function is U-shaped if it has local maxima at the boundaries of its domain and one of these is a global maximum. A function is strictly U-shaped if it is U-shaped and quasi-convex.*

U-shapes capture the qualitative feature that switching probabilities increase towards each of the ends of the domain, i.e., in the context of  $S_{k,t}(\cdot)$  switching becomes more likely for workers with low and high expected wages. Strict U-shapes additionally ensure that the switching probability increases monotonically from its interior minimum toward the extremes of the domain. A particular property of a U-shaped function  $S$  is that  $g \circ S$  is also U-shaped whenever  $g$  is strictly monotone. This has the practical relevance that it will not matter whether we refer to the actual wage of a worker or to the rank of the worker in the wage distribution, since the rank is just a monotone transformation of the actual wage.

It is easiest to highlight why the model generates U-shapes by looking at the case where workers get paid according to expected ability (6). The wage directly reflects the worker's expected ability, as  $A = (W + \Pi_k)/P_k$ . If a worker chose occupation  $k$ , it has to be the case that his prior about his expected ability was within the relevant cutoffs, i.e.,  $A \in [B_k, B_{k+1})$ . Next period he will switch down only if his posterior falls below the cutoff  $B_k$ , he will switch up only if his posterior falls above  $B_{k+1}$ , and overall he will switch if either of these two happens. Therefore

$$S_{k,t}^-(W) = G_t(B_k|A), \quad (9)$$

$$S_{k,t}^+(W) = 1 - G_t(B_{k+1}|A) \text{ and} \quad (10)$$

$$S_{k,t}(W) = G_t(B_k|A) + 1 - G_t(B_{k+1}|A). \quad (11)$$

Consider interior occupations, i.e., occupations  $k \in \{1, \dots, K-1\}$  that are not at the extreme end of the spectrum. Since the distribution  $g_t(A'|A)$  is symmetric and quasi-concave, the switching

probability is lowest when the prior  $A$  is at the midpoint between  $B_k$  and  $B_{k+1}$  and increases the more the prior moves toward either side of the interval. Figure 9 illustrates this. The solid curve is the density  $g_t(A'|A)$  of the posterior belief  $A'$  for an agent with a prior belief at the midpoint  $A = \bar{B}_k := (B_k + B_{k+1})/2$ . For this worker it is least likely that his posterior lies outside the boundaries  $B_k$  and  $B_{k+1}$ . The dotted curve to the right is the density of the posterior for a worker starting with a prior above  $\bar{B}_k$ . He is more likely to switch because his posterior has more mass outside the “stay” interval  $[B_k, B_{k+1})$ . This is particularly clear for large intervals: agents with prior in the middle need very large shocks to induce them to leave, while agents on the boundaries only need small shocks to induce them to switch occupations. The following proposition establishes this for occupations of all sizes:

**Proposition 1 (U-Shapes in Mobility)** *Consider some interior occupation  $k$  and cohort  $t$ . The switching probability  $s_{k,t}(w)$  is U-shaped; the switching probability  $S_{k,t}(W)$  is strictly U-shaped.*

**Proof.** For the formal proof see Appendix A2. ■

For interior occupations, U-shapes are likely to persist even when we do not condition on cohort  $t$ .<sup>29</sup> For the extreme occupations of  $k = 0$  and of  $k = K$  the switching probability  $S(\cdot, t)$  is also quasi-convex, but the minimum is at the extreme of the domain: In the case of the lowest occupation workers at the bottom are least likely to switch since there is no lower occupation to switch down to, while in the case of the highest occupation workers at the top are least likely to switch because there is nothing better to move to. Therefore, U-shapes cannot be derived in models that focus on two occupations only.

Next, we describe the direction of switching. Consider some interior occupation  $k$ . Intuitively, workers with high ability within this occupation and associated high average wages are the ones that are most likely to have output realization that indicate that they are appropriate for more productive occupations. This is visible in Figure 9 because the tail of the distribution that exceeds the upper bound increases as the distribution is shifted to the right. Workers with low belief about their mean ability are more likely to find out that they are not good enough and should move to a

---

<sup>29</sup> This can be easily proved for the wage setting process (5), because extreme wages reflect extreme updates no matter what cohort the worker is in, and so switching probabilities approach one for extreme wages across cohorts and are lower for intermediate wages. Under (6), there is still a tendency for U-shapes unconditional on cohort, yet it is possible to construct examples where U-shapes do not hold for all occupations. The reason is that at the same expected ability older workers have more precision and switch less. If young workers are mainly in the middle of the interval  $[B_k, B_{k+1})$  while old workers are more at one side, this composition effect between cohorts can lead workers with interior abilities (and wages) to switch more than those with abilities that are a bit more to the side.

less productive occupation. Such a switch might manifest itself through firing if the employer has the same information as the worker, or as a quit due to the fact that the wage in absence of high performance is not good enough in the current occupation. The following proposition formalizes this intuition about switching behavior. It characterizes the probability for upward and downward switches conditional on switching. If the switching probability  $S_{k,t}(W) > 0$ , then the conditional probability of switching up is  $S_{k,t}^+(W)/S_{k,t}(W)$ , and similar for downward switches.<sup>30</sup>

**Proposition 2 (Direction of Sorting)** *Consider workers of cohort  $t$  in interior occupation  $k$  that switch. Among these, higher wage workers are more likely to switch up and lower wage workers are more likely to switch down:  $s_{k,t}^+(w)/s_{k,t}(w)$  is increasing and  $s_{k,t}^-(w)/s_{k,t}(w)$  is decreasing;  $S_{k,t}^+(W)/S_{k,t}(W)$  is increasing and  $S_{k,t}^-(W)/S_{k,t}(W)$  is decreasing.*

**Proof.** We focus on the wage setting process (6); see Appendix A2 for (5). Recall that a worker earns wage  $W$  only if he has belief  $A = (W + \Pi_k)/P_k$ . By (10) we can write  $S_{k,t}^+(W) = 1 - G_t(B_{k+1}|A) = 1 - G_t(B_{k+1} - A|0)$ , where the second equality follows from lateral adjustment. Since  $G_t(\cdot|0)$  is a CDF, it is increasing, and so  $-G_t(B_{k+1} - A|0)$  is increasing in  $A$ , and thus in  $W$ . By a similar argument  $S_{k,t}^-(W)$  is decreasing in  $W$ . This immediately implies that  $S_{k,t}^+(W)/(S_{k,t}^-(W) + S_{k,t}^+(W))$  is increasing, while  $S_{k,t}^-(W)/(S_{k,t}^-(W) + S_{k,t}^+(W))$  is decreasing. ■

Therefore, this simple model about learning one's absolute advantage generates the main predictions about sorting that we documented in the data. These results also hold in terms of wage residuals when we control for more variables than just labor market experience. For example, we might also want to condition on occupational tenure. While conditioning on a particular occupational tenure changes the distribution of workers across the various ability levels, it does not change the insight on the shape of sorting since workers who are closer to a cutoff will still switch for smaller increments in information than workers in the middle, and it neither changes the robust insights on the direction because workers close to the upper cutoff are still more likely to get shocks that lead them to switch upwards than other workers.

### 3.3 Other Implications of the Model

In this section we derive and contrast with the data several additional implications of the model. Before turning to some implications that are specific to our equilibrium theory, we review two standard results from the learning literature. These have important implications for understanding the earnings process. First, we point out that our learning model is obviously able to account

---

<sup>30</sup>It is easy to show that  $S_{k,t}(W) > 0$  for all  $W$ . Yet it can be that case that  $s_{k,t}(w) = 0$ , and then  $s_{k,t}^+(w) = s_{k,t}^-(w) = 0$ . In this case, notational consistency in the following proposition requires a convention about conditional probabilities. In this case it is convenient to define the conditional probability of switching up or down as  $s_{k,t}^+(w)/s_{k,t}(w) = s_{k,t}^-(w)/s_{k,t}(w) = 1/2$ .

for the fact that switching probabilities decline with age, a pattern documented in Appendix OA10, but also visible in, e.g., Figure 2(b) in the main text. Second, the model can reproduce the important empirical pattern that cross-sectional variance in wages increases with labor market experience. This pattern has received much attention in the literature, going back to, e.g., Mincer (1974). The fact that the learning model captures these features so naturally makes it a strong candidate for modeling the process (3) by which  $A_t$  evolves.

*Younger workers of cohort  $t$  switch more often than older workers of cohort  $t' > t$ , as long as  $t'$  is sufficiently large.* This well-known result follows immediately from the fact that over time worker's information becomes more precise. Therefore, for any given belief  $A$  about one's mean ability and associated wage  $W$ , the likelihood that this prior will change substantially given the new output realization is lower for older workers. That is,  $S_t(W)$  is decreasing in  $t$  and older workers switch less conditional on the same ability (same expected wage).<sup>31</sup>

*Under our learning process, if wages are paid according to expected ability (6), the cross-sectional variance in wages for young workers (cohort  $t$ ) is smaller than for older workers (cohort  $t' > t$ ).*<sup>32</sup> Exactly because the information about each individual becomes more precise, the wages in (6) diverge for older workers. Since the ability of young workers is not very precise, they get similar wages. As information gets revealed in the production process, it becomes clearer which workers have high ability and which have low ability, and the former get paid more while the latter get paid less. Thus, their remuneration naturally fans out. Process (5) is analytically less tractable since the variance in the distribution of mean ability is confounded with the variance in the output process.<sup>33</sup>

### 3.3.1 Other Implications of the Model: Theory

We also obtain additional predictions specific to our model by considering wages of workers of the same cohort who switch occupations relative to those who stay in an occupation. It is clear that

---

<sup>31</sup>Since the distribution of abilities is different for older workers, it is theoretically possible that a particular older generation  $t'$  has abilities that are more concentrated around some switching cutoff  $B_k$  and therefore they switch more than a younger generation  $t$ . This is not possible as  $t'$  becomes large because information becomes nearly perfect while concentration does not go up substantially around any cutoff given our normal distribution assumptions, and we did not find any such effect in any of our simulations.

<sup>32</sup>It is easy to verify that the wage schedule  $W(A) = \max_k W_k(A)$  are convex in expected ability. So mean-preserving spreads of the distribution of expected ability increase the variance of wages. The result follows since younger workers know less about their ability:  $F_{t'}(A)$  is a mean-preserving spread of  $F_t(A)$  when  $t' > t$ . To see this, note that Footnote 26 showed that  $F_t$  is normal with mean  $\mu_a$  and precision  $\frac{\phi_a + t\phi_\varepsilon}{t\phi_\varepsilon} \phi_a$ , and the latter is monotonically decreasing in  $t$ .

<sup>33</sup>Under (5), if there exists only one occupation the variance in wages would be unchanged as workers simply obtain a wage equal to their innate ability plus shock, multiplied by  $P_1$ . With multiple occupations, if workers start mainly in occupation  $k$  initially most output realizations are multiplied by  $P_k$ , but later generations sort better and low abilities get multiplied by smaller productivities  $P_{k'} < P_k$  while higher abilities get multiplied by higher productivities  $P_{k''} > P_k$ , which tends to increase the variance.

our model can generate the pattern regarding the wage changes that we reported in Section 2.4: upward switchers tend to see higher wage increases than workers who remain in the occupation, who in turn see higher wage increases than workers who switch down. This immediately arises if wages are set according to (6) but depends on parameters when wages are set according to (5).<sup>34</sup> More robust predictions of the model that are independent of whether the wage setting process is assumed to be given by (5) or (6) involve the comparison of wage levels between occupational switchers and stayers.

When we compare wages of workers who start in the same occupation, but some switch and some stay, we obtain the following prediction:

**Proposition 3** *Consider workers of the same cohort, and compare the wages in period  $t + 1$  for those who stayed in occupation  $k$  with the wages of those workers who switched from  $k$  to  $k'$  between periods  $t$  and  $t + 1$ : The average wage of the stayers is higher than the average wage of downward switchers ( $k' < k$ ), but is lower than the average wage of upward switchers ( $k' > k$ ).*

**Proof.** Workers' beliefs about their mean ability are strictly ranked as follows: workers who switch up do so because their belief went up above  $B_{k+1}$ , while workers who stayed have a belief in  $[B_k, B_{k+1})$ , and workers who switched down have a belief below  $B_k$ . The result follows immediately because expected wages are increasing in the belief. ■

A less immediate implication arises when we compare switchers and stayers, but consider those that end up in the same occupation. Here, the predictions are exactly reversed:

**Proposition 4** *Consider workers of the same cohort  $t$ , and any occupations  $k$  and  $k'$  that are not too large or too far apart (i.e.,  $\max\{|B_{k'+1} - B_k|, |B_{k+1} - B_{k'}|\} \leq \sqrt{\phi_{t+1}/(\phi_\epsilon + \phi_t)}$ ). Compare the wages in period  $t + 1$  for those who stayed in occupation  $k'$  with the wages of those workers who switched from adjacent occupation  $k$  to  $k'$  between periods  $t$  and  $t + 1$ . The average wage of the stayers in  $k'$  is lower than the average wage of downward switchers (i.e., if  $k > k'$ ), but is higher than the average wage of upward switchers (i.e., if  $k < k'$ ).*

**Proof.** See Appendix A2. ■

The logic behind this result is the following. Consider downward switchers. They enter the new occupation from above, and their expected ability is more concentrated at the upper end of

---

<sup>34</sup>Wages set according to (6) strictly increase in expected ability. Since a worker only switches up if the assessment of his ability improved more than the assessment of ability for those people who stay, the wage of a worker who switches up improves more than for those how stay. A similar argument applies to workers who switch down. This pattern is less obvious if wages are set according to (5) because of reversion to the mean: a worker who had a particularly good shock will switch up to get his output multiplied by a higher productivity but will likely not have such a good shock again (and therefore not such high output) next period.

interval  $[B_{k'}, B_{k'+1})$  relative to the expected abilities of the workers who were in this occupation all along. The qualifier that the occupations are not too far apart ensures that updates are within one standard deviation of the distribution of updates, which guarantees that the distribution in this range is concave. It is a sufficient condition used in the proof, but is not necessary.

Thus, the predictions about the relative wages of stayers vs. switchers depend in an interesting way on the definition of stayers. This provides us with observable implications that can be verified in the data.

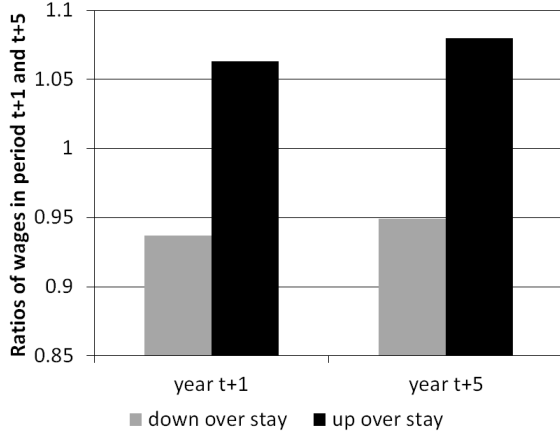
### 3.3.2 Other Implications of the Model: Evidence

To assess the empirical validity of the implication in Propositions 3, we compare the wage levels of stayers to those of switchers in a year or five years after the switch. Consider all workers in occupation  $k$  in period  $t$ . In period  $t + 1$  (or  $t + 5$ ) we compute the ratio of wages of workers who left occupation  $k$  for a higher ranking occupation to wages of those who remained in occupation  $k$  between  $t$  and  $t + 1$ . Similarly, we compute the ratio of year  $t + 1$  or  $t + 5$  wages of workers who left occupation  $k$  for a lower ranking occupation in period  $t + 1$  to wages of those who remained in occupation  $k$  between  $t$  and  $t + 1$ . Next, we compute the average of these ratios across all occupations weighted by the number of workers in each occupation who switched either up or down. Figure 10(a) presents the results. The wage ratio of up-switchers over stayers is above 1, which indicates that the wages in period  $t + 1$  of workers who switch up from  $t$  to  $t + 1$  is higher than the wage of workers who stayed from period  $t$  to  $t + 1$ . The wage ratio of down-switchers over stayers is below 1 indicating that workers who switched to lower ranking occupations have lower wages after the switch than workers who stayed in the same original occupation. This is consistent with the predictions of Proposition 3. Figure 10(b) shows that the ranking implied by Proposition 3 remains consistent with the data when we also condition on number of years after graduation in addition to being in occupation  $k$  in period  $t$ . The comparison of wages five years after the switch indicates that these effects are highly persistent.<sup>35</sup>

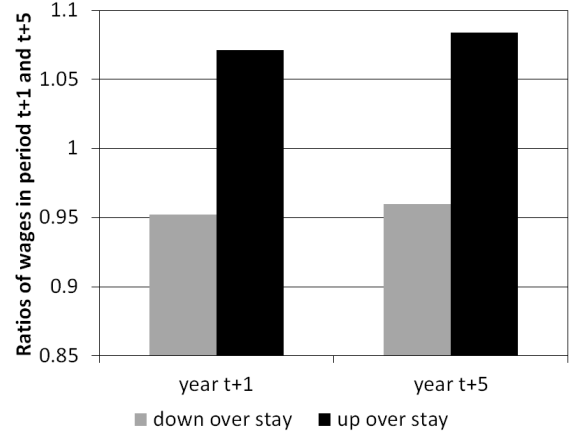
To assess empirically the predictions of Proposition 4, we compare wages of switchers into occupation  $k'$  to wages of those who stayed in occupation  $k'$  between  $t$  and  $t + 1$ . In Figure 11(a) we construct the weighted average of period  $t + 1$  wage ratios of switchers into occupation  $k'$  over stayers in occupation  $k'$ . Figure 11(a) illustrates that workers who switched to higher ranking occupations have lower wages after the switch than the stayers in the occupation into which the up-switchers moved and that the opposite is true for workers who switched to lower ranking occupations. Figure 11(b) illustrates that these patterns are robust to also conditioning

---

<sup>35</sup>The standard errors of the wage ratios in Figures 10 and 11 range from 0.00083 to 0.00197. Due to their small size, they are invisible in the Figures.



(a) Unconditional.



(b) Conditional on the number of years after graduation.

Figure 10: Weighted average of year  $t + 1$  or  $t + 5$  ratios of real wages of workers who switch occupations between years  $t$  and  $t + 1$  over workers who stay in the same *original* occupation in years  $t$  and  $t + 1$  by direction of the switch (i.e., whether the switch involves moving to an occupation that pays more or less on average than the source occupation.)

on the number of years after graduation. The also persist five years after the switch.

Appendix Figure OA-9 presents the results of these experiments on the Large Sample. The predictions of Propositions 3 and 4 remain consistent with the data.

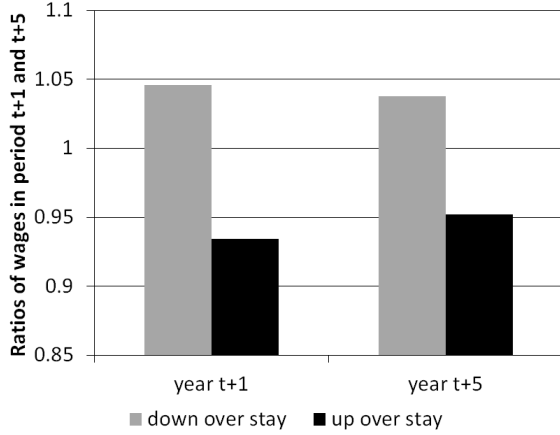
## 4 Changing Occupational Productivities

Most occupations are rather stable in their occupational ranking over time. Nevertheless, some occupations such as computer programmers in the 1990s have seen substantial wage increases for their workforce, while other occupations such as textile machine operators have seen substantial wage declines.<sup>36</sup> The associated changes in occupational rank are an indication of changing productivity at the occupational level. In light of the model, these occupations would require a different workforce as their productivity changes.

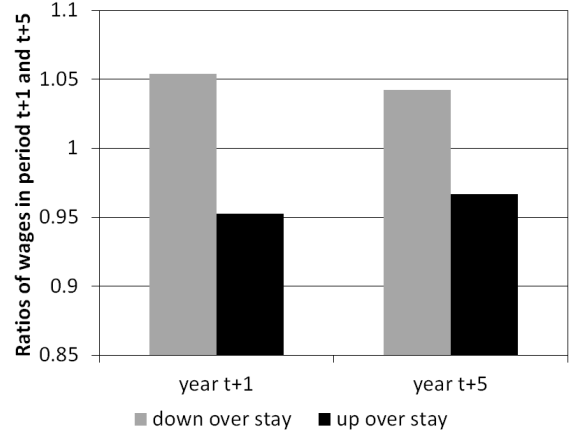
In this section we analyze how changes in occupational productivity affect occupational mobility. First, we extend the model to allow changes changes to the productivity of occupations – and see that the competition among workers for jobs implies that occupations with rising productivity attract and retain high ability (high wage) workers that drive out low ability (low wage) workers. Second, we show that this pattern is indeed present in the data for the occupations with fastest wage growth, which is the sign of fast productivity growth in the model. Opposite predictions arise for declining occupations, and these are also confirmed in the data. This captures the

<sup>36</sup>Kambourov and Manovskii (2009a) measure the magnitude of changes in occupational productivities.





(a) Unconditional.



(b) Conditional on the number of years after graduation.

Figure 11: Weighted average of year  $t + 1$  or  $t + 5$  ratios of real wages of workers who switch occupations between years  $t$  and  $t + 1$  over workers who stay in the same *destination* occupation in years  $t$  and  $t + 1$  by direction of the switch (i.e., whether the switch involves moving to an occupation that pays more or less on average than the source occupation.)

behavior for the bulk of the occupations for which we did not find U-shapes. Finally, we describe how our model relates to a stylized version of the famous Roy (1951) model that is often used as the workhorse model to analyze worker mobility in the presence of sectoral productivity shocks. This part shows why at least in the most basic setting the equilibrium nature of our model is crucial in predicting these patterns.

## 4.1 Mobility in Response to Changing Occupational Productivity: Theory

Consider our basic model, but assume from one period to the next the productivity of occupation  $k$  changes from  $P_k$  to  $P'_k > P_{k+1}$ .<sup>37</sup> This changes the ranking of occupations. Workers in occupation  $k$  who realize that they are better than expected and would have changed occupation will now stay, while workers whose ability remains constant and that would have stayed might now leave because of the competitive pressure of other workers that enter this occupation. In the absence of switching costs it is not relevant whether this change is temporary or permanent. We obtain the following result for the switching patterns for the case where firms absorb the uncertainty of

<sup>37</sup>For a more general treatment of a model where multiple occupations may have changes in productivity, see Appendix OA15. The proposition in this section carries over essentially unchanged to occupations that change their rank upward or downward relative to the other occupations. Also, note that more productive workers sort into more productive occupations, and therefore an improved productivity that does not change the ranks of occupations only changes the wages but not the ability cutoffs at which workers select in one occupation or another. This would change if there were strictly positive switching costs as then also the level of wages matters.

the production process, but a proposition with similar content can be proved when workers are residual claimants.<sup>38</sup>

**Proposition 5** *Consider an occupation  $k$  with a rise in productivity such that  $P'_k > P_{k+1}$ . If occupation  $k+1$  is no smaller than occupation  $k$  and wages are set according to (6), the probability of switching out of occupation  $k$  decreases with higher wages for workers in the same cohort.*

*Consider an occupation  $k$  with a decline in productivity such that  $P'_k < P_{k-1}$ . If occupation  $k-1$  is no smaller than occupation  $k$  and wages are set according to (6), the probability of switching out of occupation  $k$  increases with higher wages for workers in the same cohort.*

**Proof.** We prove the result for a rising occupation; analogous steps establish the result for a declining occupation. Workers are initially in occupation  $k$  because their prior  $A$  was in set  $[B_k, B_{k+1})$ . To stay in occupation  $k$ , their posterior now has to be above  $B'_k$ , which is larger than  $B_{k+1}$  since occupation  $k$  is no larger than occupation  $k+1$ . Thus, workers with a higher prior are closer to the region where they stay in  $k$ , and therefore it is more likely that their posterior falls into this region (which follows formally from single-peakedness and lateral adjustment of the update  $G_t$ ). ■

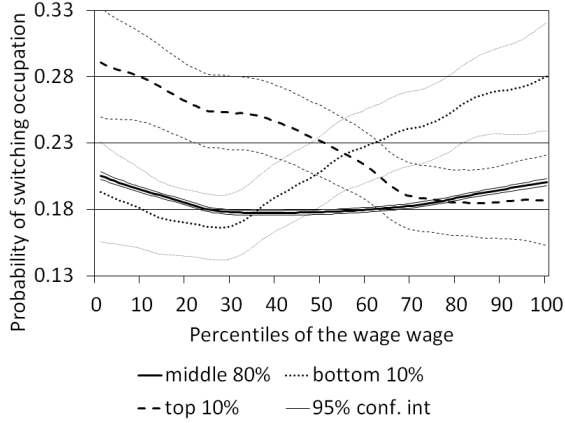
## 4.2 Mobility in Response to Changing Occupational Productivity: Evidence

Consistent with the theory, in the data we find that lower paid workers in a given occupation tend to leave it when occupational productivity rises, while higher paid workers in a given occupation are more likely to leave it when productivity of the occupation declines. We examine this in the data by studying occupations with different average wage growth between years  $t$  and  $t+1$ . Similar to Section 2.3 we compute the average wage based on either the raw wages or wage residuals. For each of these two notions of the average wage, we calculate the percent increase between each two consecutive years between 1995 and 2002.

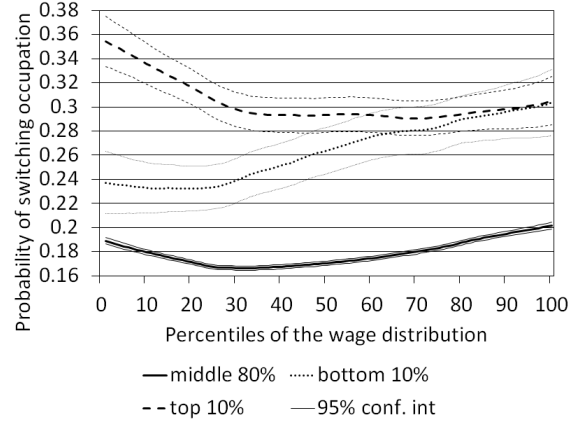
Figure 12 plots three groups of occupations, separated by the growth rates of average wages between years  $t$  and  $t+1$ . The first group consists of the 10 percent of occupations with the lowest growth rates, the second group is the 10 percent of occupations with the highest growth rates, and the third group is the occupations with growth rates in average occupational wages in the middle 80 percent. For the three different occupational groups we plot the probabilities of switching

---

<sup>38</sup>For wages set according to (5) we can prove the following. Consider an occupation  $k$  with a rise in productivity such that  $P'_k > P_{k+1}$ . If occupation  $k+1$  is no smaller than occupation  $k$  and wages are set according to (6), then only some of the workers with wages above the occupational mean stay, while all lower wage workers leave. For a decline in productivity, all workers above the mean leave and only some below stay. For the proof please see the more general version of this result in the appendix.



(a) Distribution of raw wages within occupation and year. Growth rates of average wage in occupation from population.



(b) Distribution of wages residuals. Growth rates of average wage in occupation from time constants in wage regression.

Figure 12: Non-parametric plot of probability of switching occupation by worker's percentile in the relevant wage distribution. For the fastest growing 10% of occupations, the slowest growing 10% of occupations, and the remaining 80% of occupations.

occupation as a function of the workers' position in wage distribution in their occupation in year  $t$ . Figures 12(a) and 12(b) show that workers in occupations with the lowest growth rate of wages between  $t$  and  $t + 1$  have a higher probability of leaving their occupation between  $t$  and  $t + 1$  if they are from the upper end of the occupational wage distribution in year  $t$ . Workers in the fast growing occupations have a higher probability of leaving their occupation if they are in the lower part of the wage distribution in their occupation. Workers in occupations that grow faster than the slowest growing 10 percent but slower than the fastest growing 10 percent, have a probability of changing occupation that is U-shaped in their wage percentile.

The results of the corresponding analysis on the Large Sample are reported in Appendix Figure OA-10. They clearly exhibit the same qualitative patterns.

### 4.3 The Relation to the Roy Model in the Presence of Shocks

Our model is related to the popular Roy (1951) model. That model was designed to investigate the impact of shocks on the sorting of workers and their wages. It might be instructive to highlight briefly the commonalities and differences. To see the commonality, consider the following version of the Roy model formalized in Heckman and Honore (1990), simplified to two occupations 1 and 2 with output prices  $P_1$  and  $P_2$ , respectively.<sup>39</sup> Each worker is endowed with a two-dimensional skill set  $(s_1, s_2)$  that describes his output in each occupation. Each worker chooses the occupation where he obtains the highest payoff, i.e., he chooses Occupation 1 if  $P_1 s_1 > P_2 s_2$ . Figure 13(a)

<sup>39</sup>The later sections in Heckman and Honore (1990) also discuss in detail identification with multiple occupations.

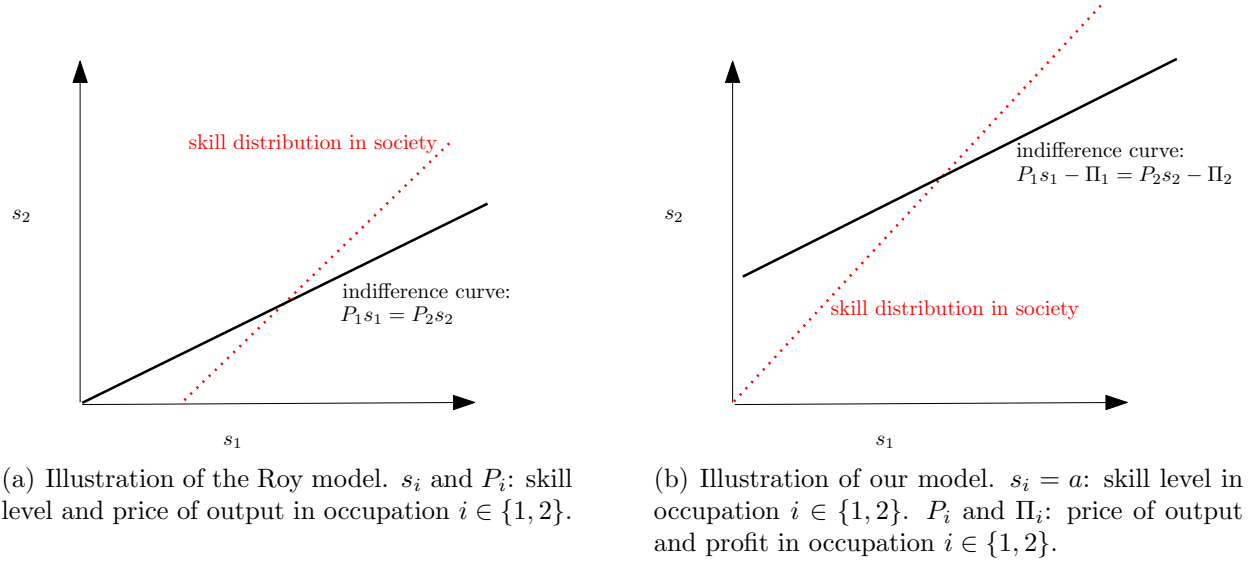


Figure 13: Comparison between Roy model and our model for fixed productivities  $P_1$  and  $P_2$ .

illustrates this. The solid line through the origin depicts all skill combinations  $(s_1, s_2)$  where the workers are exactly indifferent between each occupation, and workers with skill combinations to the right obtain a higher return in Occupation 1 and so choose it, while to the left they choose Occupation 2. The dotted line indicates the skill distribution in the special case where this is a straight line. Its slope indicates absolute advantage in the sense that a worker who is good in one occupation is also good in the other.<sup>40</sup> Our model resembles the Roy model with absolute advantage: In our specification workers choose Occupation 1 if  $P_1s_1 - \Pi_1 > P_2s_2 - \Pi_2$  as indicated in Figure 13(b), and all skills are on the diagonal line since  $(s_1, s_2) = (A, A)$ . Without shocks it simply constitutes a rotation of the basic Roy model. In that case the main additional feature of our model is learning about skills, which implies that an agents position on the the solid line is not fixed over time, which generates mobility.

Another important difference between the models arises in the presence of shocks to prices (occupational productivities), which is the only source of mobility in the basic Roy model. If the low productivity occupation  $P_1$  improves, then the solid line becomes steeper. In the case of absolute advantage, the worst workers in Occupation 2 will leave and become the highest wage workers in Occupation 1, as depicted in Figure 14(a). Note that there is no competition among workers for jobs: A worker can create a job for himself in either occupation independently of the choices of other workers, so some workers that used to choose Occupation 1 now create a job for

<sup>40</sup>In contrast to absolute advantage, relative advantage indicates a line where workers that are better in one occupation are not as skilled in the other. Note that most applied work goes beyond a straight line to consider a distribution of skills, such as a joint-normal where the direction of the correlation of skills gives an indication of absolute or relative advantage.

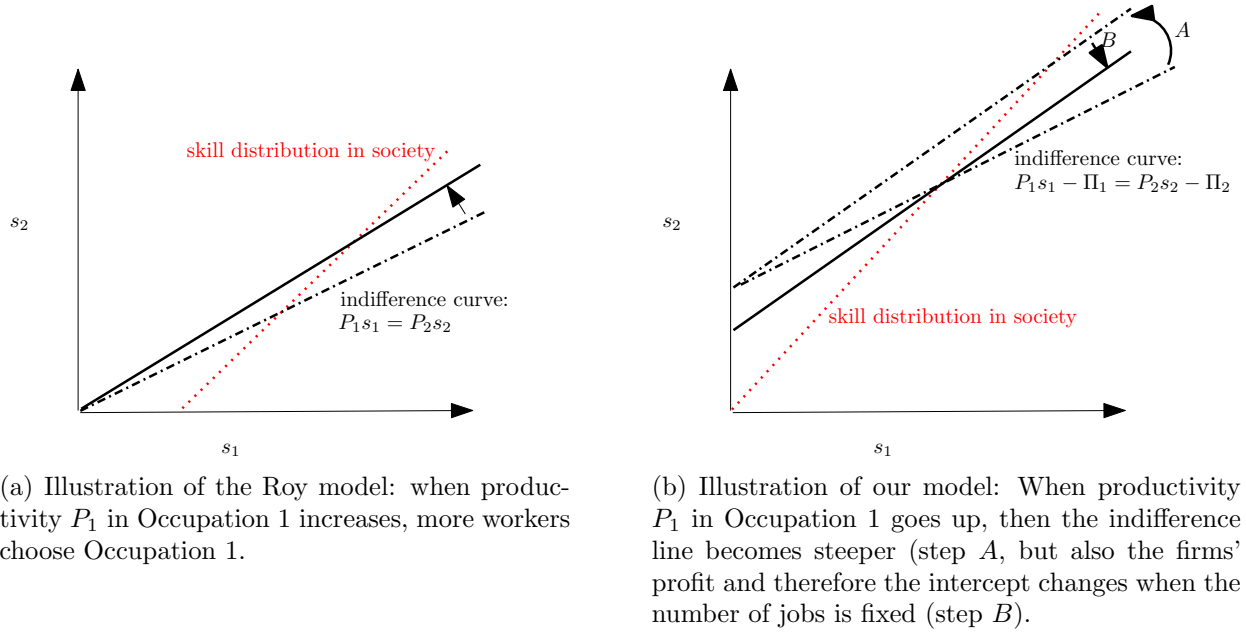


Figure 14: Comparison between Roy model and our model when productivity  $P_1$  increases.

themselves in Occupation 2, but none of the workers who used to choose Occupation 2 would now create their job in Occupation 1. This is a general feature of the basic Roy model even if skills are not just concentrated on one line.<sup>41</sup> This is very different in our setting. The immediate effect of an increase in  $P_1$  in our model is similar: the line that divides who selects into which occupation becomes steeper, as indicated in step A in Figure 14(b). This would be the only change if profits would remain constant (or if workers could create jobs for themselves at cost  $\Pi_k$ ). Yet since jobs in each occupation are limited, it cannot be that more workers can choose a given occupation, which is reflected in an increase of profits of the firms and therefore a decrease in the intercept as depicted by step B in Figure 14(b). The competition among workers for the fixed number of jobs means that exactly the same skills select into each occupations as before, unless the solid curve becomes steeper than the skill distribution (which happens when occupations reverse rank, i.e.,  $P_1 > P_2$ ). In this case the matching pattern reverse: while high ability workers used to select into occupation 2, they now select into occupation 1. Therefore, only those workers who learned that they are sufficiently able stay in occupation 1 while the rest is driven out by incoming high-ability workers, while only those workers that learned that they are not very able stay in occupation 2 while the rest leaves for the now more attractive occupation 1. These are the effects described in Section 4.1. Clearly, if there are costs to switching occupations the change of the workforce would not be as abrupt as discussed here. Also, as occupations become more productive they

<sup>41</sup>Nevertheless, in a Roy model with three or more occupations, a simultaneous productivity shock to multiple occupations might give rise to very general patterns, the study of which is beyond the scope of this paper.

might indeed expand in size, but if it becomes increasingly expensive to create more positions the results of this discussion still apply (see Appendix OA16 for details).

## 5 Conclusion

Using administrative panel data on 100% of Danish population we document a new set of facts characterizing the patterns of occupational mobility. We find that a worker’s probability of switching occupation is U-shaped in his position in the wage distribution in his occupation. It is the workers with the highest or lowest wages in their occupations who have the highest probability of leaving the occupation. Workers with higher (lower) relative wage within their occupation tend to switch to occupations with higher (lower) average wages. Higher (lower) paid workers within their occupation tend to leave it when relative productivity of that occupation declines (rises) steeply.

To account for these patterns we suggest that it might be productive to think of occupations as forming vertical hierarchies. Complementarities between the productivity of an occupation and the ability of the workers induces workers to sort themselves into occupations based on their absolute advantage. Since their absolute advantage is not fully known initially, they update on their ability after observing their output and re-sort themselves according to the update. Employment opportunities in each occupation are scarce, inducing competition among workers for them. We present an equilibrium model of occupational choice with these features and show analytically that it is consistent with patterns of mobility described above.<sup>42</sup>

This theory captures the patterns of occupational mobility in a very parsimonious model. In particular, it generates the patterns of “promotions” and “demotions” observed in the data. An investigation of the occupational classification suggests that both of these switches up or down the occupational hierarchy represent real occupational changes in the sense that the required skill set changes substantially. Moreover, it is essential to take the pattern of selection implied by the model into account to estimate the returns to occupational tenure, interpret earnings dynamics, and to assess the effects of economic policies. While neither models of learning in the absence of occupational differentiation (horizontal learning) nor models solely of comparative advantage generate the data patterns that we find, a tractable combination of the two accounts well for the observed pattern. We also show that standard upward career progression due to human capital accumulation can easily be integrated into the framework, yet by itself fails to account for the downward movements observed in the data.

---

<sup>42</sup>In Appendix OA14.4 we integrate the notion of jobs into the model, and find that a theory of firm mobility driven by occupational moves (rather than occupational mobility driven by firm moves) seems to account well for the data patterns that we document when conditioning on staying with or switching firms.

The analysis in this paper shows the qualitative ability of the model to account for the new data patterns that we find (and for a number of patterns documented in prior work). Our simulations suggest that the model might also generate the right quantitative magnitudes, and might provide a fruitful way to think about selection issues in the presence of occupational mobility. Taking the model and its extension to human capital in Section OA14.2 and Appendix OA17 as given, adaptations of existing econometric methods allow to control for selection and to estimate the human capital process.<sup>43</sup>

In terms of the future agenda, the main objective is to explore more fully its quantitative implications. In particular, while we think that the vertical sorting mechanism we described is an important part of any comprehensive theory of occupational mobility, it appears unlikely that it accounts for the full extent of occupational mobility. The main goal in this agenda will be to embed and distinguish different economic forces – such as learning, fluctuations in occupational productivities or demands, and search frictions in locating jobs in various occupations<sup>44</sup> – in a dynamic general equilibrium model of occupational choice and to quantitatively evaluate their contribution to the amount of occupational mobility observed in the data. The key challenge in this regard is to identify the sets of occupations forming distinct hierarchies in the data and the extent of transferability of skills across occupations within and across these hierarchies, which might also require a broader notion of skills beyond the one-dimensional measure that we use in our basic model.<sup>45</sup> For example, one hierarchy could be electrical equipment assembler, electrician, electrical engineer, and manager. Another could be truck driver, taxi driver, motor vehicle mechanic, and sales representative. Yet another could be an economics consultant, economics professor, and dean. It is likely that switches within and across these hierarchies are present in the data. It is also likely that human capital is not equally transferable within and between hierarchies. Developing a way to identify such hierarchies in the data and the transferability of human capital between them seems essential to enable future quantitative analysis.

---

<sup>43</sup>As discussed in Section OA14.2, we provide direct evidence on occupational switching assumed in partial equilibrium with related payoff structure by Gibbons, Katz, Lemieux, and Parent (2005). They argue that lagged variables that are valid instruments for occupational choice within the structure.

<sup>44</sup>If agents cannot instantaneously change jobs, but have to go through a search phase before they find a new job, adjustment based on new information is not instantaneous. Nevertheless, if search frictions are sufficiently small the allocation is close to the competitive outcome that we outline in this work and we expect the basic properties to carry over (for convergence when the periods between search activities becomes small see for example Atakan (2006) and for convergence when the short side of a market gets matched with near certainty see Eeckhout and Kircher (2010)).

<sup>45</sup>Note that the parameters of the stationary environments in Section 3 and Section OA16 such as occupational productivity  $P_k$ , profits  $\Pi_k$  and human capital accumulation functions  $H(t)$  and  $h_k(\tau)$  can be consistently estimated using the methodology proposed by Gibbons, Katz, Lemieux, and Parent (2005) even if the econometrician does not know exactly which occupation belongs to which hierarchy. It suffices that the workers know this. If they stay within distinct hierarchy, their past choices serve as instruments. However, if the environment is not stationary (as in Section 4) or if switching occurs also across hierarchies, further investigation is necessary.

## References

- ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): “High Wage Workers and High Wage Firms,” *Econometrica*, 67(2), 251–334.
- ALVAREZ, F., AND R. SHIMER (2009): “Unemployment and Human Capital,” mimeo, University of Chicago.
- ATAKAN, A. E. (2006): “Assortative Matching with Explicit Search Costs,” *Econometrica*, 74(3), 667–681.
- BECKER, G. (1973): “A Theory of Marriage: Part I,” *Journal of Political Economy*, 81(4), 813–846.
- BILS, M., AND K. J. MCLAUGHLIN (2001): “Interindustry Mobility and the Cyclical Upgrading of Labor,” *Journal of Labor Economics*, 19(1), 94–135.
- CHAMLEY, C. P. (2004): *Rational Herds: Economic Models of Social Learning*. Cambridge University Press.
- DAHL, C., D. LE MAIRE, AND J. MUNCH (2009): “Wage Dispersion and Decentralization of Wage Bargaining,” Discussion Paper No. 09-15, University of Copenhagen.
- ECKHOUT, J., AND P. KIRCHER (2010): “Sorting and Decentralized Price Competition,” *Econometrica*, 78(2), 539–574.
- (2011): “Identifying Sorting – In Theory,” *The Review of Economic Studies*, 78(3), 872–906.
- GAUTIER, P. A., AND C. N. TEULINGS (2006): “How Large Are Search Frictions?,” *Journal of the European Economic Association*, 4(6), 1193–1225.
- GIBBONS, R., AND L. F. KATZ (1992): “Does Unmeasured Ability Explain Inter-Industry Wage Differentials,” *Review of Economic Studies*, 59(3), 515–535.
- GIBBONS, R., L. F. KATZ, T. LEMIEUX, AND D. PARENT (2005): “Comparative Advantage, Learning, and Sectoral Wage Determination,” *Journal of Labor Economics*, 23(4), 681–724.
- GIBBONS, R., AND M. WALDMAN (1999): “A Theory of Wage and Promotion Dynamics Inside Firms,” *Quarterly Journal of Economics*, 114(4), 1321–1358.
- GROES, F. (2010): “Occupational Experience, Mobility, and Wages: Patterns in the Danish Data,” Manuscript, Copenhagen Business School.



- HAGEDORN, M., T. H. LAW, AND I. MANOVSKII (2012): “Identifying Equilibrium Models of Labor Market Sorting,” Working Paper 18661, National Bureau of Economic Research.
- HALL, R. E., AND R. KASTEN (1976): “Occupational Mobility and the Distribution of Occupational Success among Young Men,” *American Economic Review, Papers and Proceedings*, 66, 309–315.
- HECKMAN, J. J., AND B. E. HONORE (1990): “The Empirical Content of the Roy Model,” *Econometrica*, 58(5), 1121–1149.
- JOHNSON, W. R. (1978): “A Theory of Job Shopping,” *Quarterly Journal of Economics*, 92(2), 261–278.
- JOVANOVIĆ, B. (1979): “Job Matching and the Theory of Turnover,” *Journal of Political Economy*, 87(5), 972–990.
- JOVANOVIĆ, B., AND Y. NYARKO (1997): “Stepping Stone Mobility,” *Carnegie-Rochester Conference Series on Public Policy*, 46(1), 289–326.
- KAMBOUROV, G., AND I. MANOVSKII (2005): “Accounting for the Changing Life-Cycle Profiles of Earnings,” mimeo, The University of Pennsylvania.
- (2008): “Rising Occupational and Industry Mobility in the United States: 1968-1997,” *International Economic Review*, 49(1), 41–79.
- (2009a): “Occupational Mobility and Wage Inequality,” *Review of Economic Studies*, 76(2), 731–759.
- (2009b): “Occupational Specificity of Human Capital,” *International Economic Review*, 50(1), 63–115.
- LOPES DE MELO, R. (2009): “Sorting in the Labor Market: Theory and Measurement,” Working paper, University of Chicago.
- LUCAS, R. J., AND E. PRESCOTT (1974): “Equilibrium Search and Unemployment,” *Journal of Economic Theory*, 7, 188–209.
- MCCALL, B. P. (1990): “Occupational Matching: A Test of Sorts,” *Journal of Political Economy*, 98(1), 45–69.
- MILLER, R. A. (1984): “Job Matching and Occupational Choice,” *Journal of Political Economy*, 92(6), 1086–1120.

- MINCER, J. (1974): *Schooling, Experience, and Earnings*. Columbia University Press, New York, NY.
- MOSCARINI, G. (2001): “Excess Worker Reallocation,” *Review of Economic Studies*, 68, 593–612.
- MOSCARINI, G., AND K. THOMSSON (2007): “Occupational and Job Mobility in the US,” *Scandinavian Journal of Economics*, 109(4), 807–836.
- MOUW, T., AND A. L. KALLEBERG (2010): “Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s,” *American Sociological Review*, 75(3), 402–431.
- NEAL, D. (1999): “The Complexity of Job Mobility Among Young Men,” *Journal of Labor Economics*, 17(2), 237–261.
- PAPAGEORGIOU, T. (2011): “Large Firms and Internal Labor Markets,” mimeo, Pennsylvania State University.
- (2012): “Learning Your Comparative Advantages,” mimeo, Pennsylvania State University.
- ROY, A. D. (1951): “Some Thoughts on the Distribution of Earnings,” *Oxford Economic Papers*, 3(2), 135–146.
- SHAW, K. (1984): “A Formulation of the Earnings Function Using the Concept of Occupational Investment,” *Journal of Human Resources*, 14, 319–40.
- (1987): “Occupational Change, Employer Change, and the Transferability of Skills,” *Southern Economic Journal*, 53, 702–19.
- SICHERNAM, N., AND O. GALOR (1990): “A Theory of Career Mobility,” *Journal of Political Economy*, 98(1), 169–192.
- WILK, S. L., AND P. R. SACKETT (1996): “Longitudinal Analysis of Ability - Job Complexity Fit and Job Change,” *Personnel Psychology*, 49(4), 937–967.

## APPENDICES

### A1 Appendix Tables

Table A-1: Summary statistics for the Large and Small samples and subsamples.

	Small Sample		Large Sample	
	Sample A	Sample B	Sample A	Sample B
Number of observations	485,859	449,517	1,292,932	1,229,339
Number of occupations	243	154	324	242
Age	29.58	29.42	33.25	33.20
Occupational tenure	4.21	4.21	4.54	4.57
Occupational spell number	1.73	1.71	2.30	2.30
Occupational switchers	0.19	0.18	0.19	0.18
Employer tenure	3.88	3.84	2.78	2.77
Employer switchers	0.20	0.21	0.15	0.15
Industry tenure	3.32	3.30	3.78	3.79
Years after graduation	6.37	6.28	9.56	9.54
12 years of school or less	0.74	0.75	0.65	0.66
13 years of school or more	0.26	0.25	0.35	0.34
Hourly wage in DKK in 1995	168.47	167.30	172.66	172.29
Married	0.30	0.29	0.42	0.42
Number of children	0.70	0.68	0.94	0.94

Note – The table contains the descriptive summary statistics of the Large and Small samples defined in the main text. For each of the two main samples two subsamples A and B are defined. Sample A imposes a restriction that there are at least 10 workers in an occupation in a given year. Sample B imposes a restriction that there are at least 10 workers from the same cohort (defined by the year of completing education) in an occupation in a given year.

Table A-2: Frequency of various occupational transitions and the associated wage changes.

	Type of occupational transition between years $t$ and $t + 1$			
	Year $t + 1$		Year $t + 5$	
	Switch up	Switch down	Switch up	Switch down
<i>All Workers</i>				
Wage change	1.93 (0.13)	-0.94 (0.14)	6.57 (0.48)	1.73 (0.53)
Fraction of all workers	0.104	0.084	0.114	0.084
<i>Firm stayers</i>				
Wage change	0.70 (0.15)	-0.64 (0.16)	4.46 (0.55)	0.46 (0.64)
Fraction of firm stayers	0.080	0.064	0.091	0.065
<i>Firm switchers</i>				
Wage change	2.08 (0.32)	-3.30 (0.34)	6.81 (0.95)	0.03 (1.04)
Fraction of firm switchers	0.195	0.160	0.215	0.166

Note — The table contains 1-year and 5-year wage changes for workers experiencing various types of occupational transitions net of the 1-year or 5-year wage change of the corresponding group of occupational stayers. The wage change is measured in year  $t + 1$  or  $t + 5$  relative to year  $t$  conditional on a transition between years  $t$  and  $t + 1$ . Standard errors in parenthesis.

## A2 Omitted Proofs and Derivations

### Remainder of Proof of Proposition 1:

**Proof.** Consider first wage setting process (6) and associated switching probability  $S_{k,t}$  first. Define  $\delta_k = (B_{k+1} - B_k)/2$  to be half of the distance of interval  $[B_k, B_{k+1})$ , and recall that  $\bar{B}_k = B_k + \delta_k$ . Any other belief  $A$  can be written in terms of the distance  $\delta$  from  $\bar{B}_k$ . Then

$$\begin{aligned} & S_{k,t}(P_k \bar{B}_k - \Pi_k) - S_{k,t}(P_k(\bar{B}_k + \delta) - \Pi_k) \\ &= G_t(B_k | \bar{B}_k) - G_t(B_k | \bar{B}_k + \delta) + G_t(B_{k+1} | \bar{B}_k + \delta) - G_t(B_{k+1} | \bar{B}_k) \end{aligned} \quad (A1)$$

$$\begin{aligned} &= G_t(-\delta_k | 0) - G_t(-\delta_k - \delta | 0) + G_t(\delta_k - \delta | 0) - G_t(\delta_k | 0) \\ &= \int_0^\delta [g_t(-\delta_k - \varepsilon | 0) - g_t(\delta_k - \varepsilon | 0)] d\varepsilon, \end{aligned} \quad (A2)$$

where the second equality follows from lateral adjustment. Clearly this distance is zero when  $\delta = 0$ . Symmetry around zero and single-peakedness imply that the integrand in (A2) is strictly negative for any  $\varepsilon > 0$ . Therefore, this integral is strictly negative for  $\delta > 0$ . When  $\delta < 0$  the integrand of (A2) is positive for all relevant  $\varepsilon$  but the integral is negative because of integration from zero to a negative number. The proposition obtains because integral (A2) decreases in the absolute value  $|\delta|$ .

Now consider instead the wage setting process (5). A sufficient condition for U-shapes is that switching probabilities are minimal in the interior and maximal at the boundaries. We will show that they are zero in the interior and one at the boundaries. To see this, note that when we observe the worker of cohort  $t$  in occupation  $k$  at wage  $w$ , (5), this implies that his output must have been  $X(w) = (w + \Pi_k)/P_k$ . If we knew the prior  $A$  that this person had, we could by (3) calculate his posterior as  $A' = \alpha A + (1 - \alpha)X(w)$ , where  $\alpha = \phi_t/\phi_{t+1}$ .

Since we only know the wage but do not know his prior  $A$ , we can only determine the range of priors for which the worker would switch. He switches up if  $A' \geq B_{k+1}$ , which we can rewrite as  $\alpha A + (1 - \alpha)X(w) \geq B_{k+1}$ . He switches down if  $A' \leq B_k$ , which we can rewrite as  $\alpha A + (1 - \alpha)X(w) \leq B_k$ . Since the worker chose occupation  $k$  in period  $t$ , we know that  $A \in [B_k, B_{k+1})$ . Therefore, neither of the two inequalities can be satisfied if  $X(w) \in [B_k, B_{k+1})$  or equivalently  $w \in [B_k P_k - \Pi_k, B_{k+1} P_k - \Pi_k)$ . Therefore, for such intermediate wages the switching probability  $s_{k,t}(w) = 0$ , which constitutes a local minimum.

We complete the proof by showing that for very low or very high wages within an occupation the subsequent switching probability is one. Since  $A \in [B_k, B_{k+1})$ , the condition for upward switching is satisfied for any of the priors if it holds for the lowest possible prior, i.e.,  $\alpha B_k + (1 - \alpha)X(w) \geq B_{k+1}$  which yields equivalently  $X(w) \geq \frac{B_{k+1} - \alpha B_k}{1 - \alpha}$  or  $w \geq \frac{B_{k+1} - \alpha B_k}{1 - \alpha} P_k - \Pi_k$ . So for wages above this threshold  $s_{k,t}(w) = 1$ . Similarly, the condition for downward switches is satisfied for all priors if it holds for the highest prior, which means  $\alpha B_{k+1} + (1 - \alpha)X(w) \leq B_k$  or equivalently  $X(w) \leq \frac{B_k - \alpha B_{k+1}}{1 - \alpha}$  or  $w \leq \frac{B_k - \alpha B_{k+1}}{1 - \alpha} P_k - \Pi_k$ . For such low wages again the switching

probability is  $s_{k,t}(w) = 1$ . This establishes the U-shape property.<sup>46</sup> ■

### Remainder of Proof of Proposition 2:

**Proof.** Consider workers that chose interior occupation  $k$  in their  $t^{\text{th}}$  year in the labor market. We will use the notation as in the proof of Proposition 1, and exploit the following result shown there: Workers switch only if  $X(w)$  is either below  $B_k$  or above  $B_{k+1}$ ; if they switch and  $X(w) \leq B_k$ , they switch down; if they switch and  $X(w) \geq B_{k+1}$ , they switch up. Note that  $X(w) \leq B_k$  is equivalent to  $w \leq B_k P_k - \Pi_k$ , while  $X(w) \geq B_{k+1}$  is equivalent to  $w \geq B_{k+1} P_k - \Pi_k$ . Conditional on switching, the switch will be downward with probability 1 if  $w \leq B_k P_k - \Pi_k$  and will be upward with probability 1 if  $w \geq B_{k+1} P_k - \Pi_k$ , leading to an increasing schedule. ■

### Proof of Proposition 4:

**Proof.** Consider workers with  $t$  years of labor market experience that chose occupation  $k$  and those that chose occupation  $k' > k$ . In year  $t + 1$  we compare their wages, conditional on choosing  $k'$ . All workers that we compare have some belief in  $[B_k, B_{k'+1})$  in period  $t$ , and a belief in  $[B_{k'}, B_{k'+1})$  in period  $t + 1$  of their work-life. The distribution of the update is concave in the relevant region if  $B_{k'+1} - B_k$  is not too large since normal distributions are concave around their mean. In particular, a normal distribution is concave within one standard deviation of its mean. The update has standard deviation  $\sqrt{\phi_{t+1}/(\phi_\epsilon + \phi_t)}$ , so we require  $B_{k'+1} - B_k < \sqrt{\phi_{t+1}/(\phi_\epsilon + \phi_t)}$ . Since by market clearing  $F(B_{k'+1}) - F(B_k) = \sum_{j=k}^{k'+1} \gamma_j$  this holds if the measure of firms in the occupations between  $k$  and  $k' + 1$  is not too large.

The workers' update  $A_{t+1}$  is distributed symmetrically around  $A_t$ . Since  $k' > k$ , the density  $g_t(A_{t+1}|A_t)$  of the update evaluated at any point  $A_{t+1}$  in  $[B_{k'}, B_{k'+1})$  is higher (because of symmetry and single-peakedness) and has a larger derivative (because of concavity) for any stayer (person with  $A_t \in [B_{k'}, B_{k'+1})$ ) than for any switcher (person with  $A_t \in [B_k, B_{k+1})$ ). It then follows directly that the conditional distribution of the update, conditional on  $A_{t+1} \in [B_{k'}, B_{k'+1})$ , for stayers first order stochastically dominates the distribution for switchers. The implication for expected wages follows immediately.

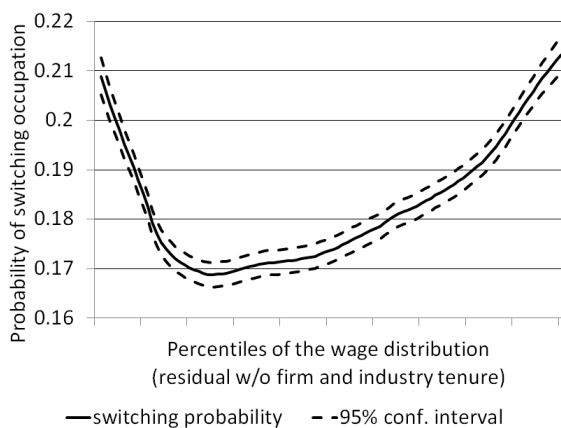
For  $k' < k$ , the condition for concavity of the update is that  $B_{k+1} - B_{k'}$  is not too large (i.e.,  $B_{k+1} - B_{k'} < \sqrt{\phi_{t+1}/(\phi_\epsilon + \phi_t)}$ ). When  $k' < k$ , the density of the update is still higher but the derivative is lower, which directly implies that the distribution for switchers first order stochastically dominates the distribution for stayers. ■

---

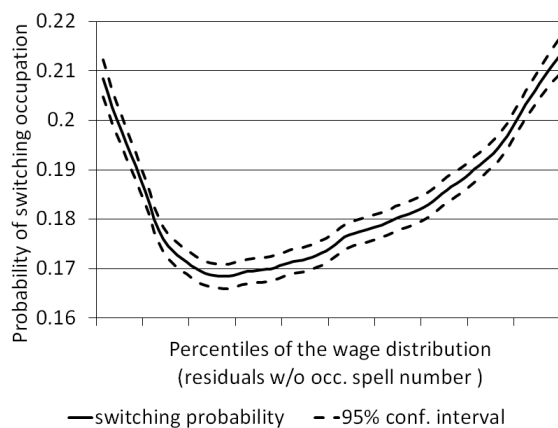
<sup>46</sup>It does not establish strict U-shapes for  $s_{k,t}$ , even though the range of priors at which the workers will switch expands with the distance of the wage from the “no-switching” region  $[B_k P_k - \Pi_k, B_{k+1} P_k - \Pi_k]$ . Consider a wage realization  $w > B_{k+1} P_k - \Pi_k$  and a different wage realization  $w' > w$ . After the first, agents with priors in  $(A, B_{k+1})$  switch for some  $A$ , while after the latter agents with priors in  $(A', B_{k+1})$  switch, and  $A' < A$  because at the higher wage updating is stronger. While this might suggest that more agents switch after  $w'$ , this need not be true. The probability that the prior is in  $(A, B_{k+1})$  conditional on observing  $w$  may in fact be higher than the probability that the prior was in  $(A', B_{k+1})$  conditional on realizing wage  $w'$ . One can construct examples where this happens, and in such a case more agents switch after  $w$  than after  $w'$ . This arises because the conditional probability does not have to be monotone.

ONLINE APPENDIX to  
 “The U-Shapes of Occupational Mobility”  
 by Fane Groes, Philipp Kircher, and Iourii Manovskii

## OA1 Alternative Wage Regression Specifications



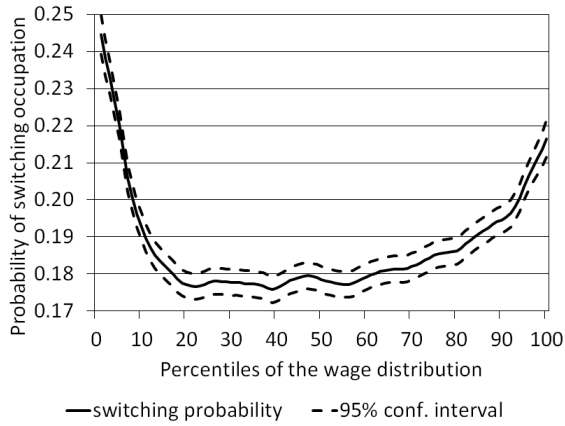
(a) Wage regression excluding firm and industry tenure.



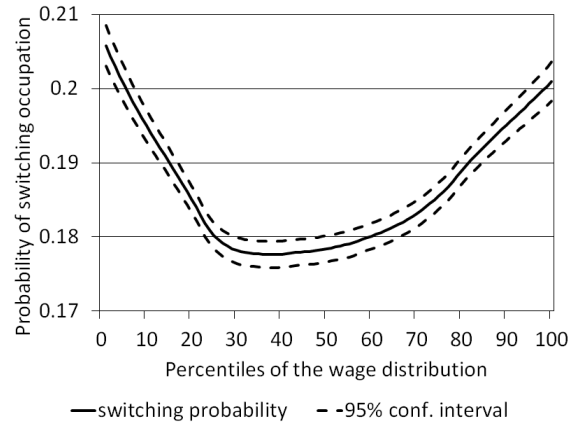
(b) Wage regression excluding occupational spell number.

Figure OA-1: Non-parametric plot of probability of switching occupation by worker's percentile in residual distributions from alternative wage regression specifications.

## OA2 Sensitivity to Bandwidth Choice

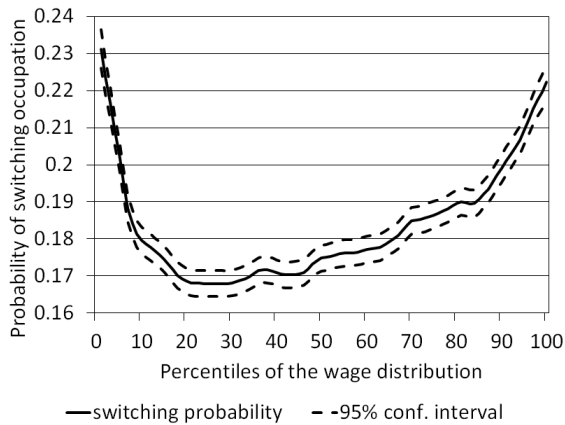


(a) Half bandwidth.

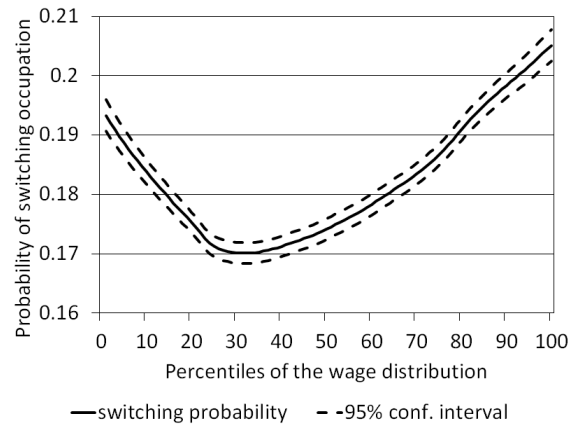


(b) Double bandwidth.

Figure OA-2: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution within occupation and year for half and double bandwidth.



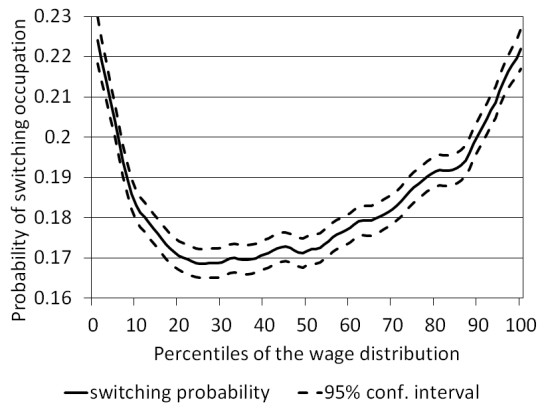
(a) Half bandwidth.



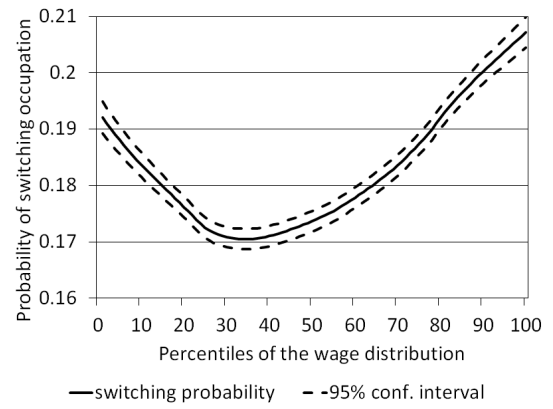
(b) Double bandwidth.

Figure OA-3: Non-parametric plot of probability of switching occupation by worker's percentile in the distribution of wage residuals for half and double bandwidth.

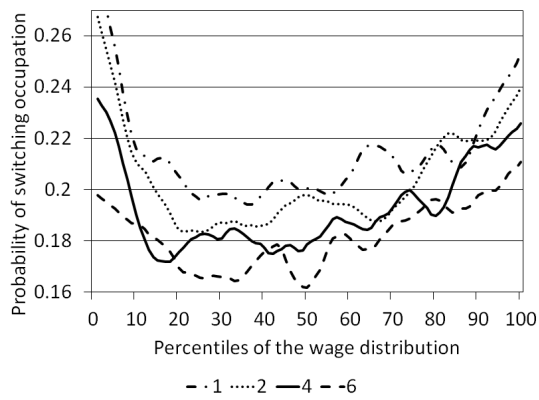




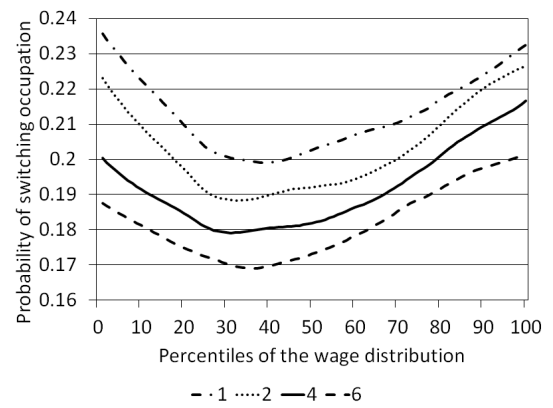
(a) Overall. Half bandwidth.



(b) Overall. Double bandwidth.



(c) For various years after graduation. Half bandwidth.



(d) For various years after graduation. Double bandwidth.

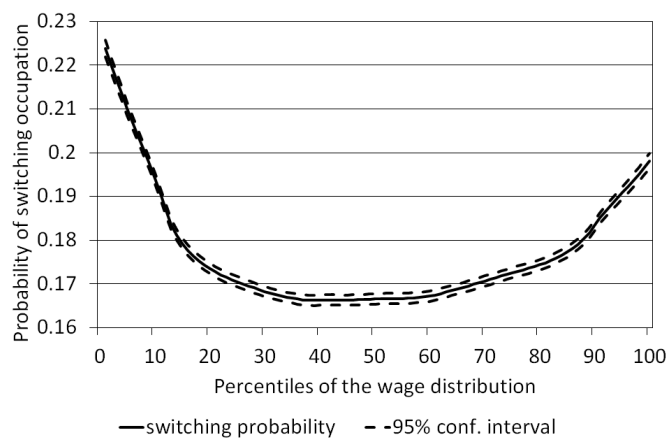
Figure OA-4: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution within occupation, year, and years after graduation for half and double bandwidth.

### OA3 Results on the Small Sample Including more Experienced Workers

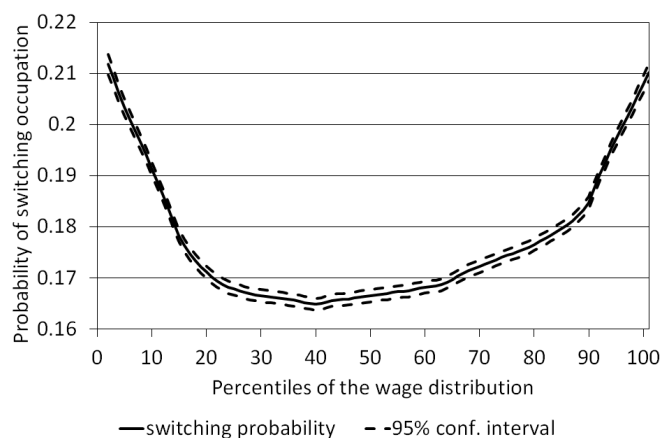
The U-shape pattern holds true for all years of experience and/or years after graduation. In Appendix OA4 we show occupational mobility for up to 15 years after graduation for our Large Sample that includes individuals working in either the private or public sector. In that analysis we have included at most 15 years after graduation because this is the longest duration we can follow workers for in our data while observing their entire work history. Observing entire work history is necessary to create occupation, industry, and firm tenure for each worker, which are used as controls in the wage regression that delivers the wage residuals.

However, if we only consider raw wages, the data allow us to look at workers for up to 25 years after they graduate from school. To accommodate this, we create a sample of workers who completed their education and work in the private sector for at least two consecutive years (the latter restriction is just to be able to define occupational switchers between two consecutive years). For these workers we compute their wage percentiles (location in the within year and occupation wage distribution) in the same two ways as we do for workers' raw wages in the paper, i.e., unconditional and conditional on years since graduation. Figure OA-5(a) shows the workers' switching probability when we calculate wage percentiles within year and occupation. Even on this population sample, where the worker's wage percentile is not conditioned on year after graduation, the switching probability is U-shaped. The U-shape in Figure OA-5(a) indicates a higher switching probability for low wage worker than for high wage workers, which may be affected by the possibility that more experienced and less mobile workers are concentrated in the upper part of the within-occupation wage distribution. This is why we also report the results that control for worker's years after graduation when constructing wage percentiles within occupation. In Figures OA-5(b) and OA-5(c) we calculate wage percentiles of the full population sample within year, occupation, AND years after graduation. These figures show that conditioning on years after graduation yields symmetric U-shapes overall as well as for all years after graduation up to 25 years.

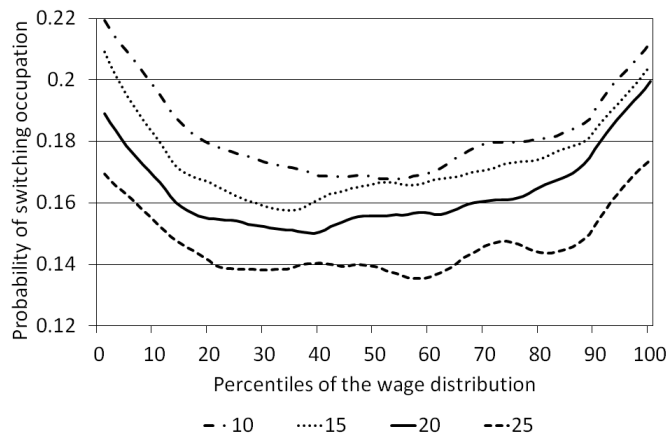
Figures OA-6(a), OA-6(b), and OA-6(c) show that our findings on the direction of mobility also remain robust for the population sample that includes experienced workers both when we find workers' wage percentiles within year and occupation and also when we calculate wage percentiles within year, occupation, and year after graduation. The directional mobility patterns follow those of Figures 3(a), 4(a), and 4(b) in the body of the paper.



(a) Distribution of raw wages within occupation and year, population.

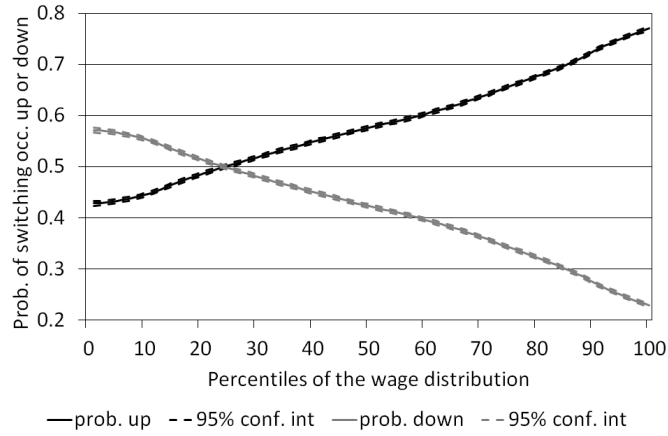


(b) Distribution of raw wages within occupation and year and year after graduation, population.

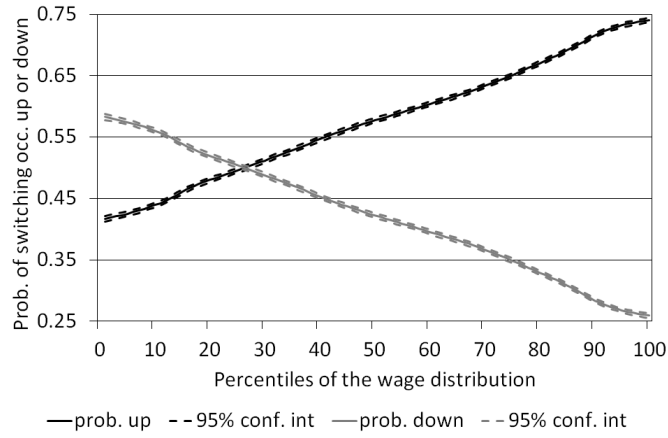


(c) Distribution of raw wages within occupation, year and 10, 15, 20, and 25 years after graduation, population.

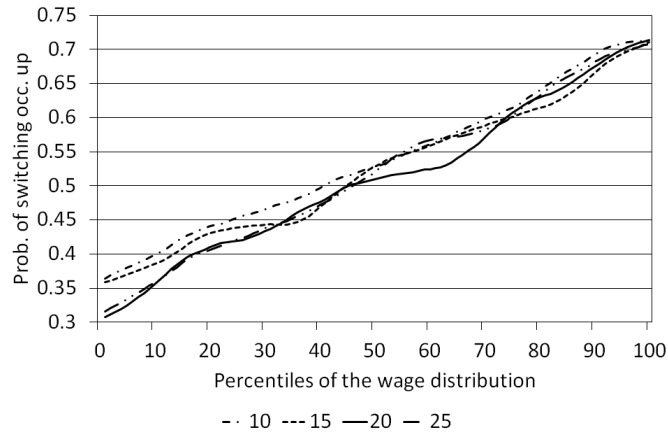
Figure OA-5: Occupation switching by worker's percentile in the relevant wage distribution before the switch for the population of workers in the private sector.



(a) Distribution of raw wages within occupation and year, population.



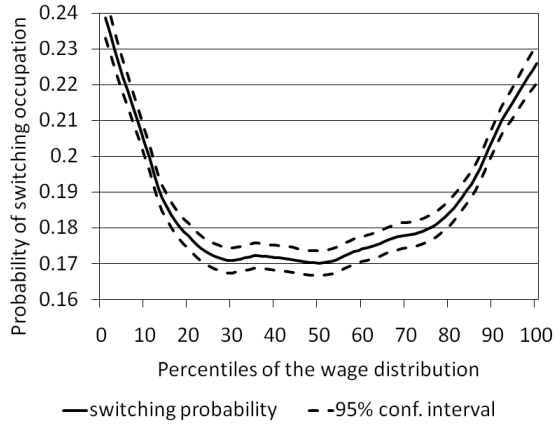
(b) Distribution of raw wages within occupation and year and year after graduation, population.



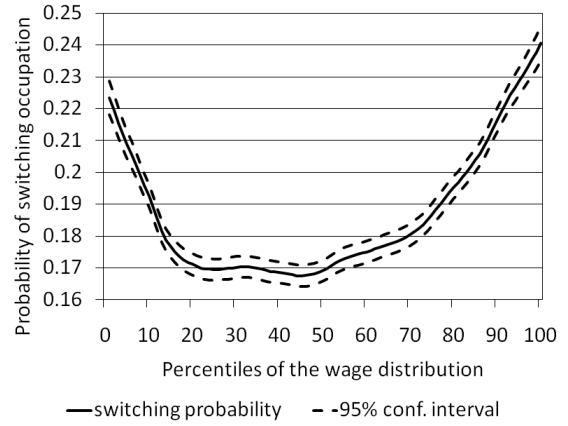
(c) Distribution of raw wages within occupation, year and 10, 15, 20, and 25 years after graduation, population.

Figure OA-6: Direction of occupational mobility, conditional on switching occupation, by worker's percentile in the relevant wage distribution before the switch for the population of workers in the private sector.

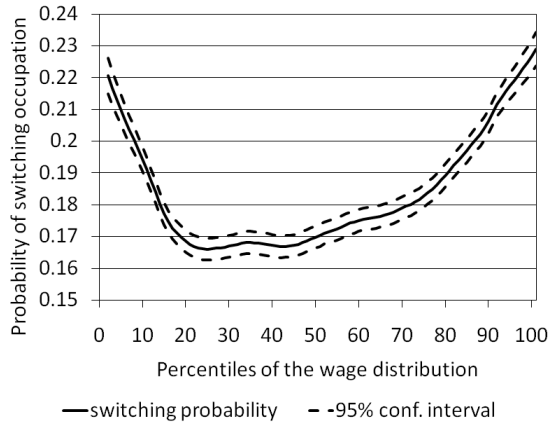
## OA4 Results on the Large Sample



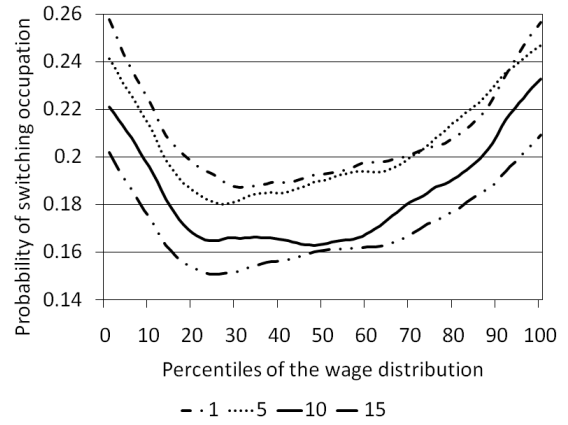
(a) Distribution of raw wages within occupation and year.



(b) Distribution of wages residuals.

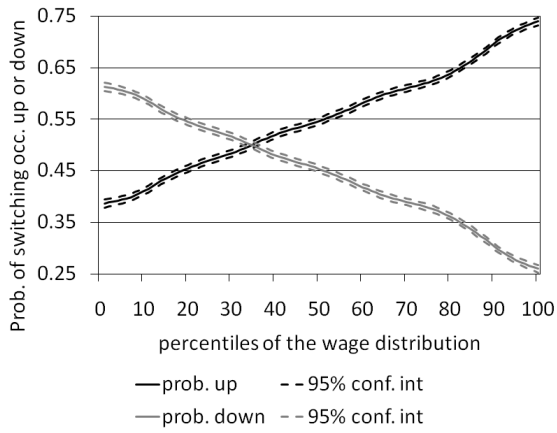


(c) Distribution of raw wages within occupation, year, and year after graduation.

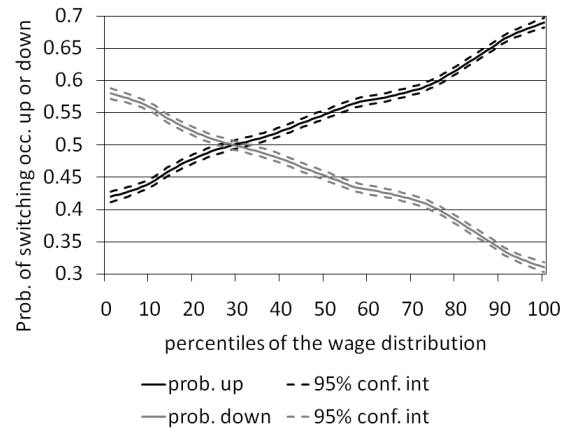


(d) Distribution of raw wages within occupation, year, and year after graduation for various years after graduation.

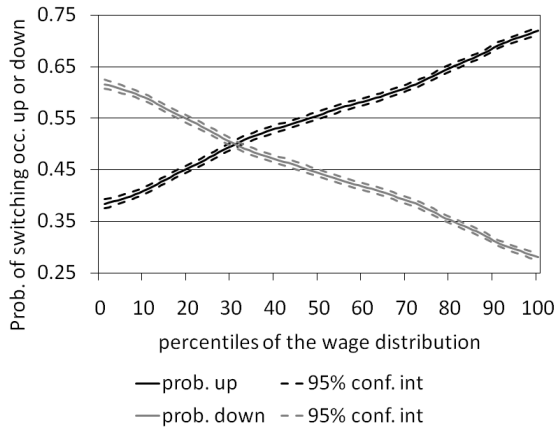
Figure OA-7: Non-parametric plot of probability of switching occupation by worker's percentile in the relevant wage distribution. Large Sample.



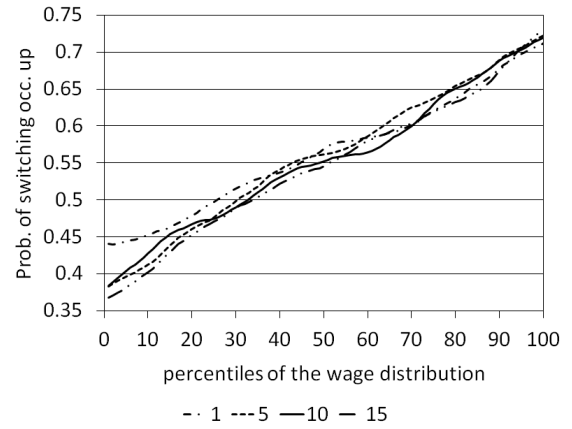
(a) Distribution of raw wages within occupation and year. Average wage in occupation from population.



(b) Distribution of wages residuals. Average wage in occupation from time constants in wage regression.

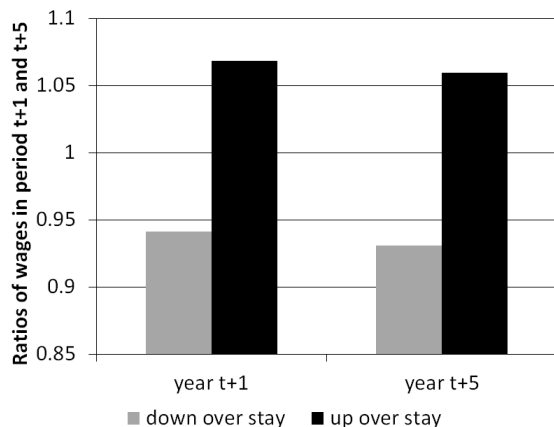


(c) Distribution of raw wages within occupation, year, and year after graduation. Average wage in occupation from population.

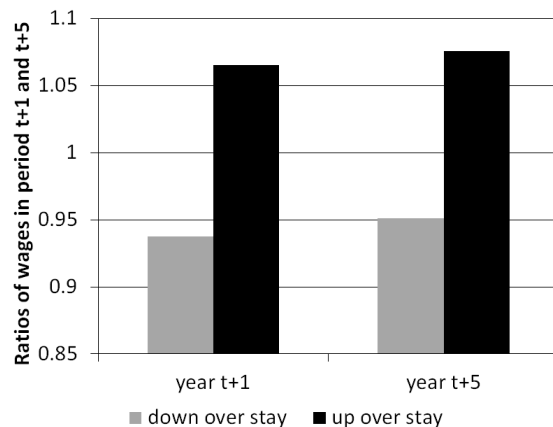


(d) Distribution of raw wages within occupation, year, and year after graduation for different years after graduation. Average wage in occupation from population.

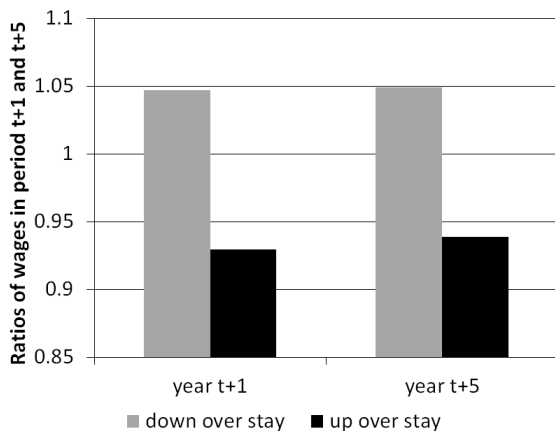
Figure OA-8: Non-parametric plot of direction of occupational mobility, conditional on switching occupation, by worker's percentile in the relevant wage distribution before the switch. Large Sample.



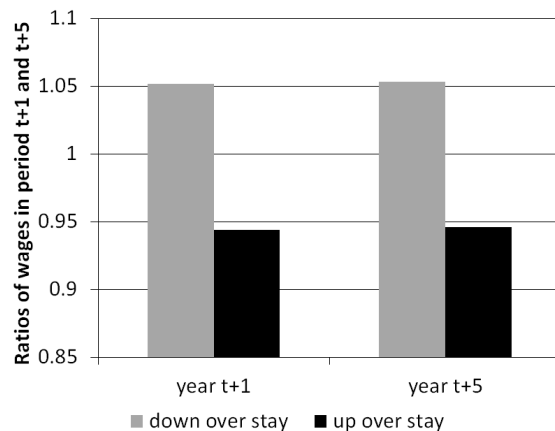
(a) Unconditional.



(b) Conditional on the number of years after graduation.

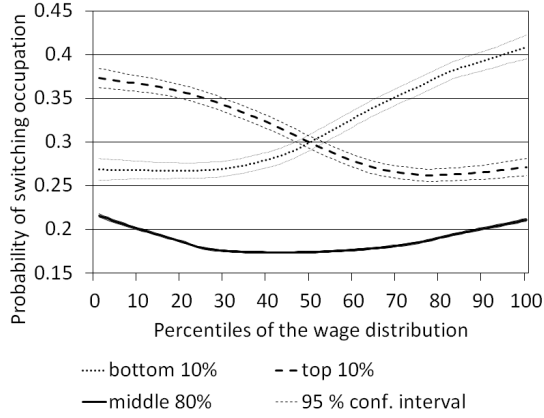


(c) Unconditional.

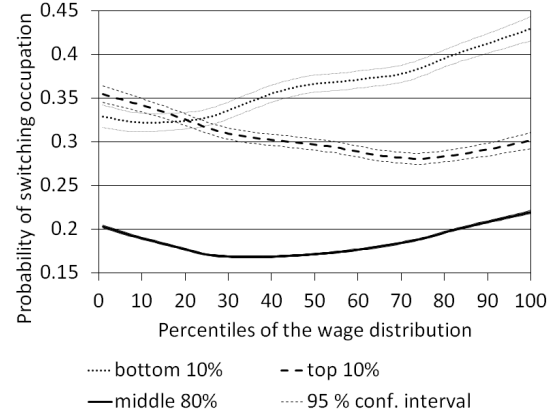


(d) Conditional on the number of years after graduation.

Figure OA-9: Weighted average of year  $t + 1$  or  $t + 5$  ratios of real wages of workers who switch occupations between years  $t$  and  $t + 1$  over (1) workers who stay in the same *original* occupation in years  $t$  and  $t + 1$  (Panels 9(a) and 9(b)) or (2) workers who stay in the same *destination* occupation in years  $t$  and  $t + 1$  (Panels 9(c) and 9(d)) by direction of the switch (i.e., whether the switch involves moving to an occupation that pays more or less on average than the source occupation). Large Sample.

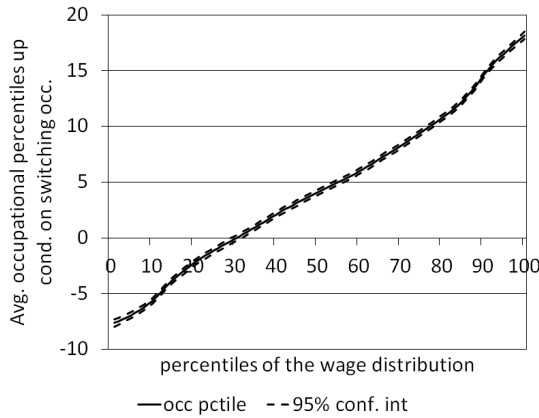


(a) Distribution of raw wages within occupation and year. Growth rates of average wage in occupation from population.

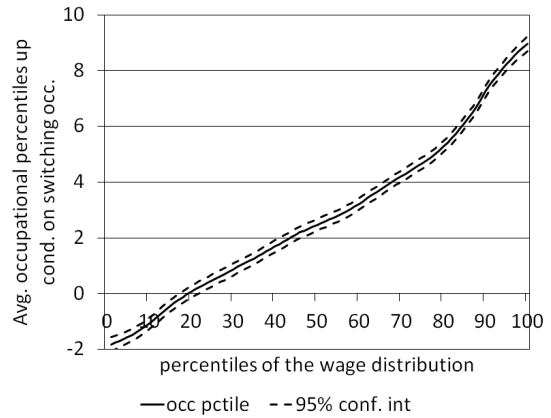


(b) Distribution of wage residuals. Growth rates of average wage in occupation from time constants in wage regression.

Figure OA-10: Non-parametric plot of probability of switching occupation by worker's percentile in the relevant wage distribution. For the fastest growing 10% of occupations, the slowest growing 10% of occupations, and the remaining 80% of occupations. Large Sample.



(a) Distribution of raw wages within occupation and year.



(b) Distribution of wage residuals.

Figure OA-11: Non-parametric plot of direction of occupational mobility in terms of change of occupational percentiles, conditional on switching occupation, by worker's percentile in the relevant wage distribution. Large Sample.



## OA5 Patterns of Occupational Mobility Within and Across Firms Conditional on Worker's Position in the Distribution of Wage Residuals

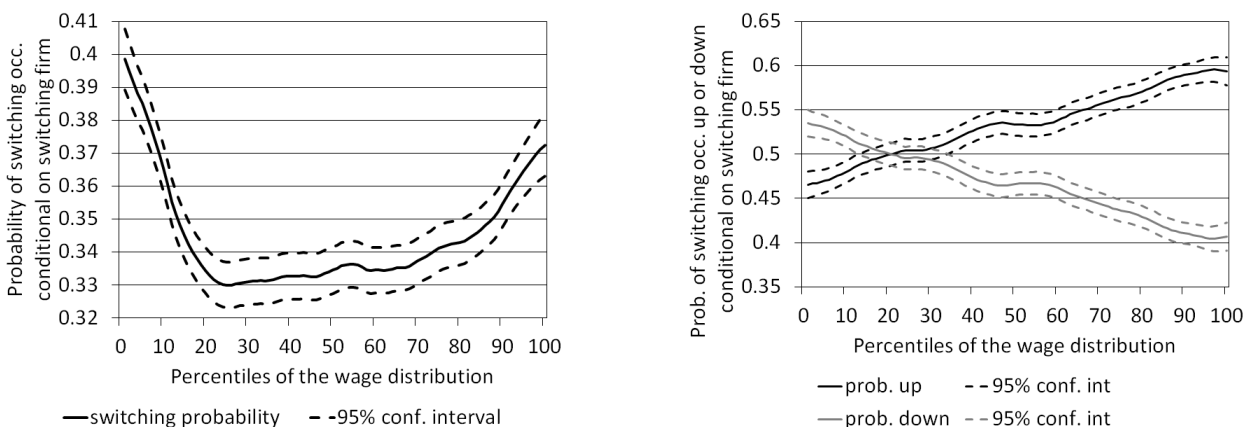


Figure OA-12: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on switching firms* by worker's percentile in the distribution residual wages.

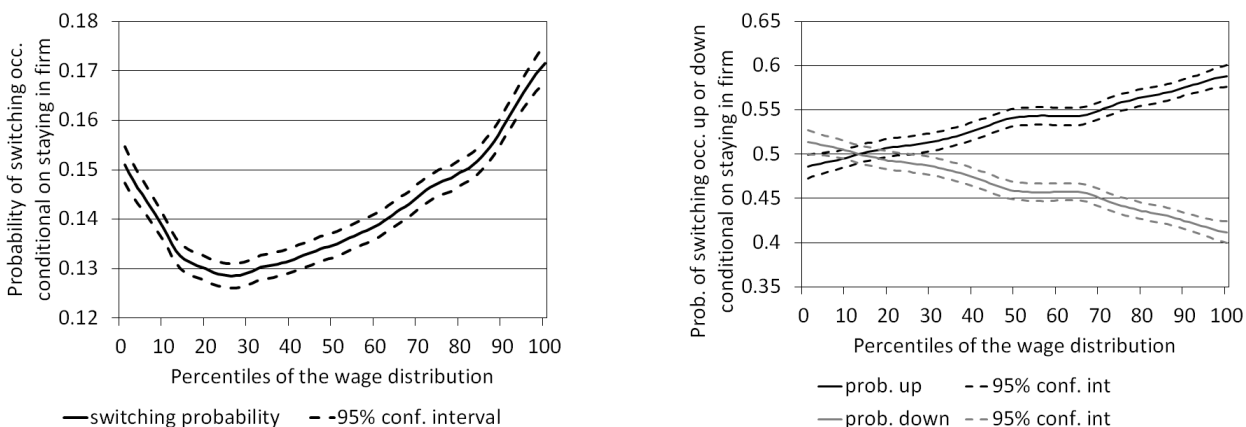


Figure OA-13: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on staying with the firm* by worker's percentile in the distribution of residual wages.

## OA6 Assessing the Role of Measurement Error

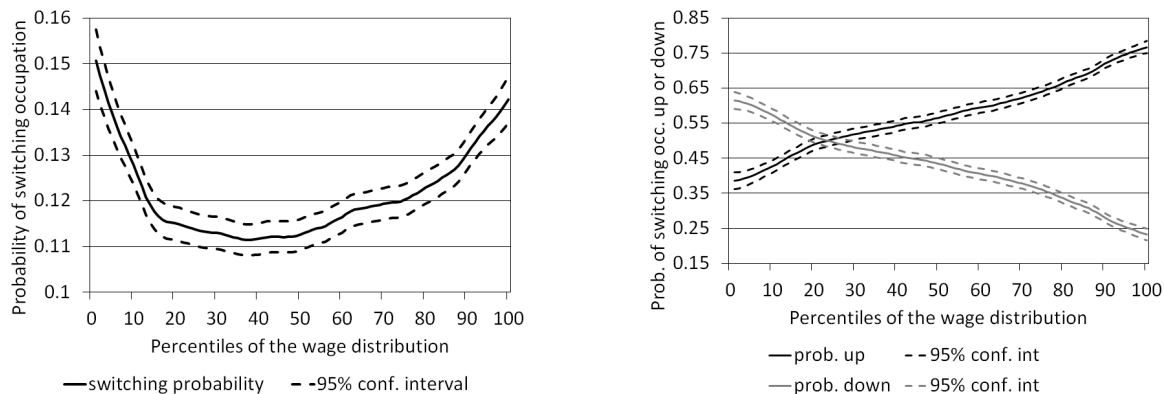


Figure OA-14: Non-parametric plots of probability of switching occupation between years  $t$  and  $t + 1$  and of direction of occupational mobility conditional on staying in the same occupation in years  $t - 1$  and  $t$  and staying the same occupation in years  $t + 1$  and  $t + 2$  by worker's percentile in the distribution of raw wages.

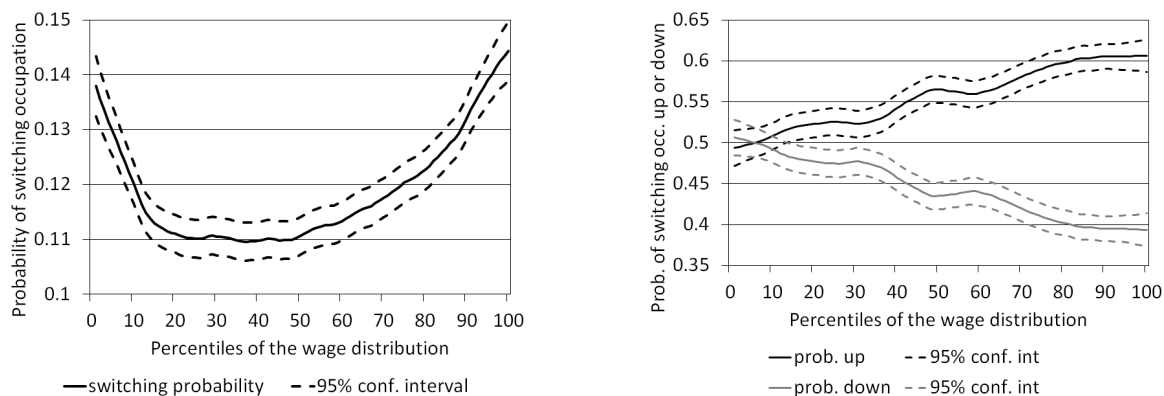


Figure OA-15: Non-parametric plots of probability of switching occupation between years  $t$  and  $t + 1$  and of direction of occupational mobility conditional on staying in the same occupation in years  $t - 1$  and  $t$  and staying the same occupation in years  $t + 1$  and  $t + 2$  by worker's percentile in the distribution of residual wages.

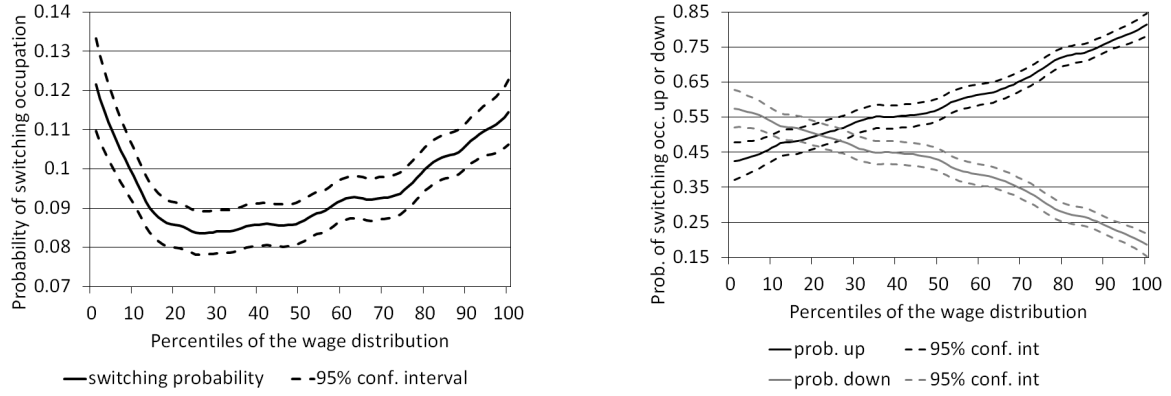


Figure OA-16: Non-parametric plots of probability of switching occupation between years  $t$  and  $t + 1$  and of direction of occupational mobility conditional on staying in the same occupation in years  $t - 2$ ,  $t - 1$ , and  $t$  and staying the same occupation in years  $t + 1$ ,  $t + 2$ , and  $t + 3$  by worker's percentile in the distribution of raw wages.

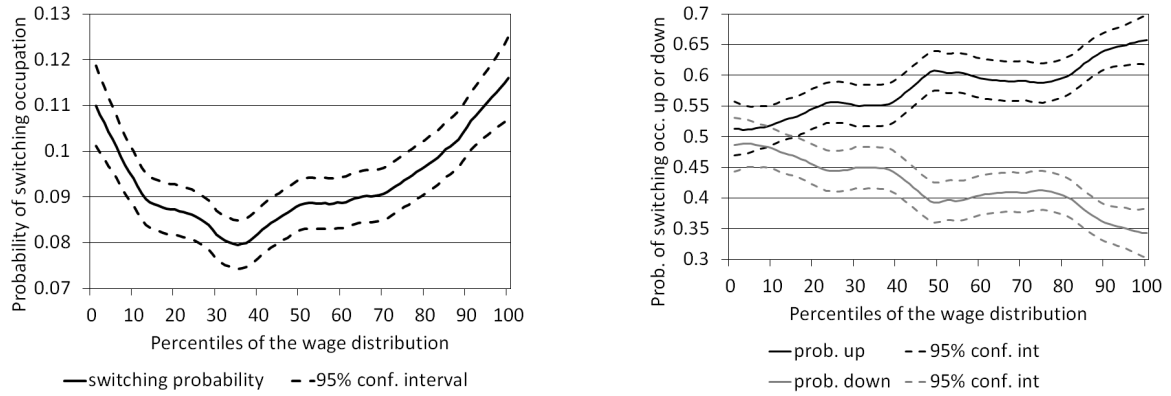
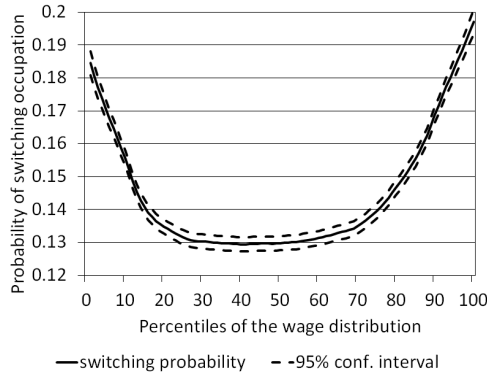
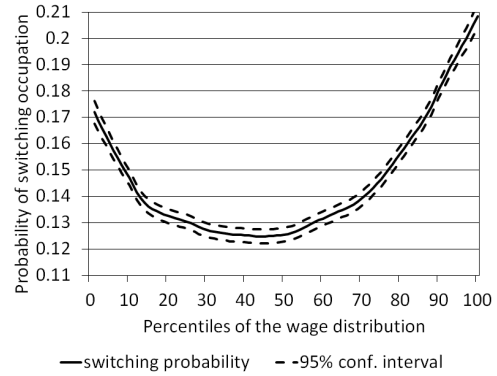


Figure OA-17: Non-parametric plots of probability of switching occupation between years  $t$  and  $t + 1$  and of direction of occupational mobility conditional on staying in the same occupation in years  $t - 2$ ,  $t - 1$ , and  $t$  and staying the same occupation in years  $t + 1$ ,  $t + 2$ , and  $t + 3$  by worker's percentile in the distribution of residual wages.

## OA7 The U-shapes of Occupational Mobility: Females

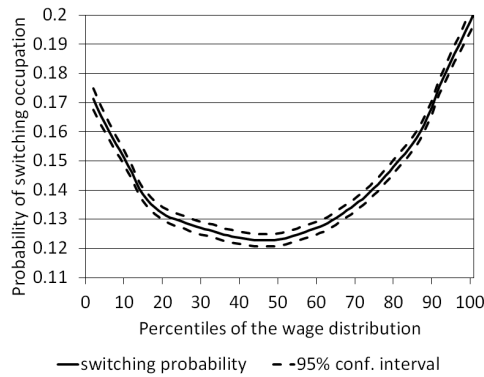


(a) Distribution of raw wages within occupation and year.



(b) Distribution of wage residuals.

Figure OA-18: Non-parametric plot of probability of switching occupation by worker's percentile in the relevant wage distribution. Women.

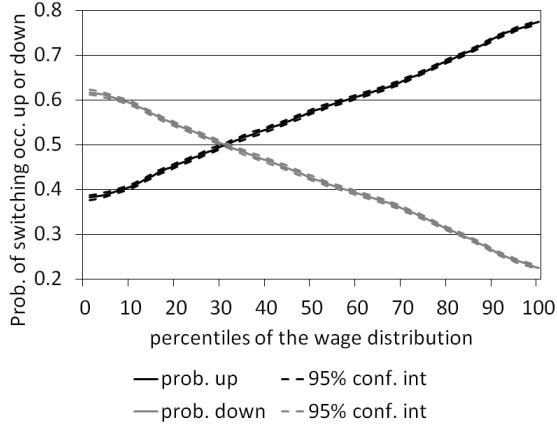


(a) Overall.

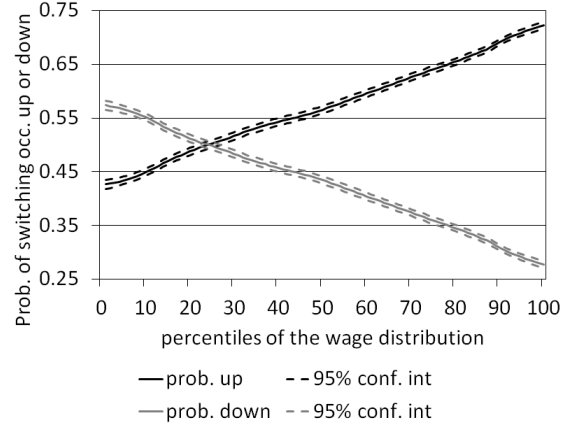


(b) For different years after graduation.

Figure OA-19: Non-parametric plot of probability of switching occupation by worker's percentile in the distribution of raw wages within occupation, year, and years after graduation. Women.

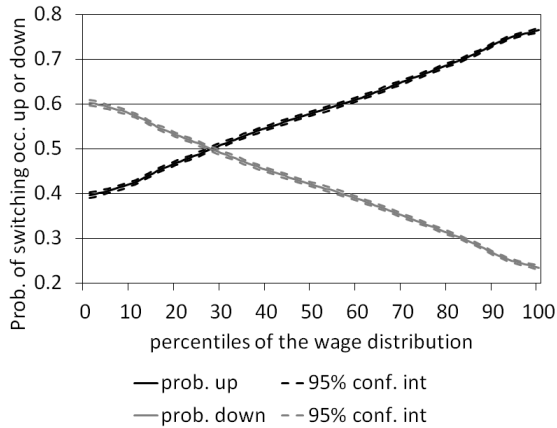


(a) Distribution of raw wages within occupation and year. Average wage in occupation from population.

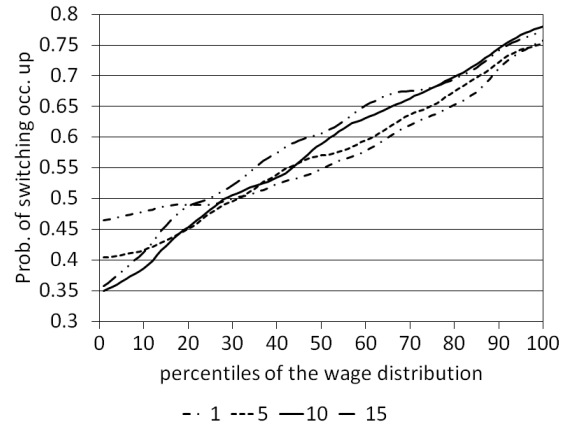


(b) Distribution of wage residuals. Average wage in occupation from time constants in wage regression.

Figure OA-20: Non-parametric plot of direction of occupational mobility, conditional on switching occupation, by worker's percentile in the relevant wage distribution before the switch. Women.



(a) Overall.



(b) For different years after graduation.

Figure OA-21: Non-parametric plot of direction of occupational mobility, conditional on switching occupation, by worker's percentile in the distribution of raw wages within occupation, year, and years after graduation before the switch. Women.

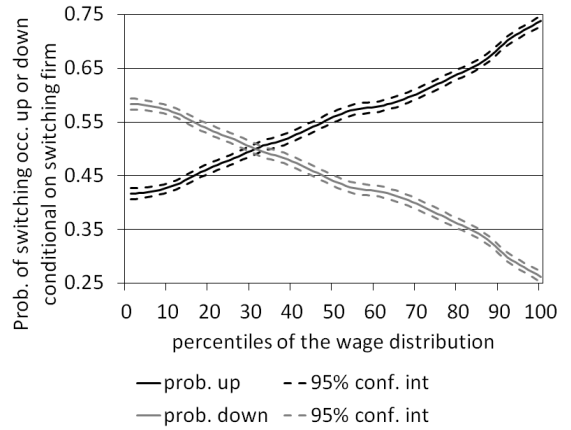
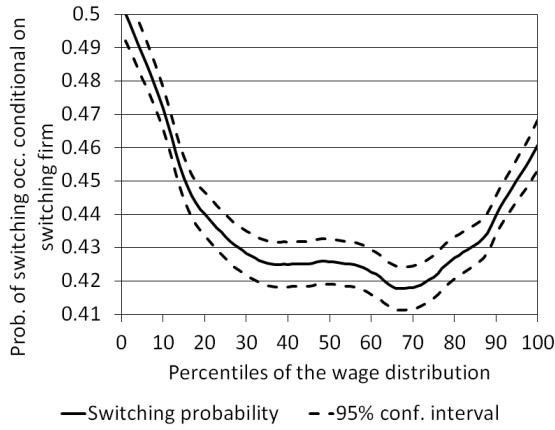


Figure OA-22: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on switching firms* by worker's percentile in the distribution or raw wages. Women.

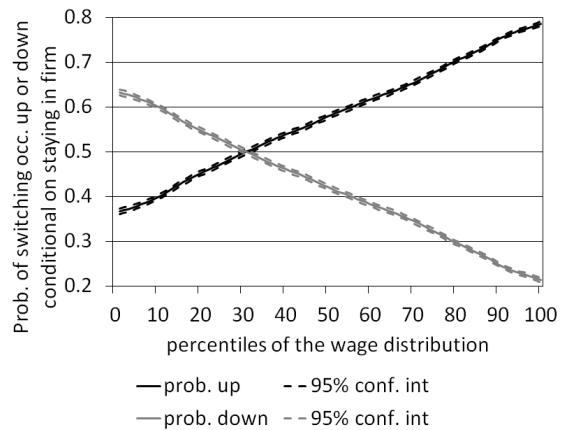
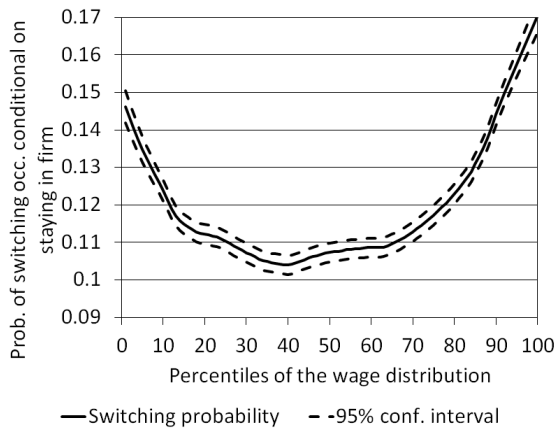


Figure OA-23: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on staying with the firm* by worker's percentile in the distribution of raw wages. Women.

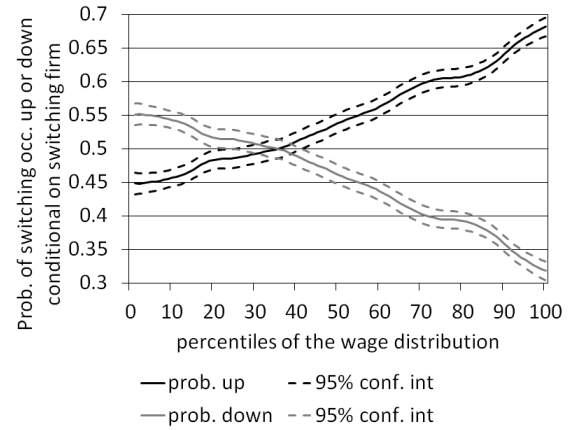
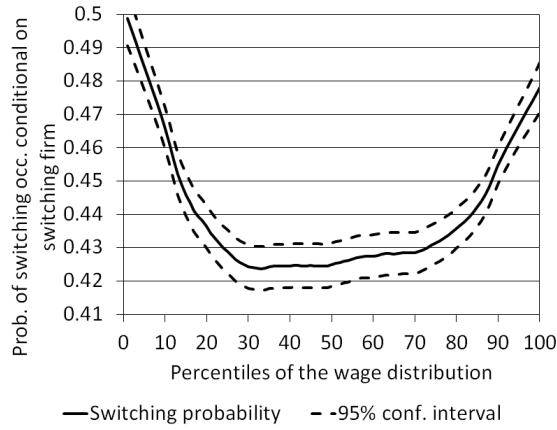


Figure OA-24: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on switching firms* by worker's percentile in the distribution residual wages. Women.

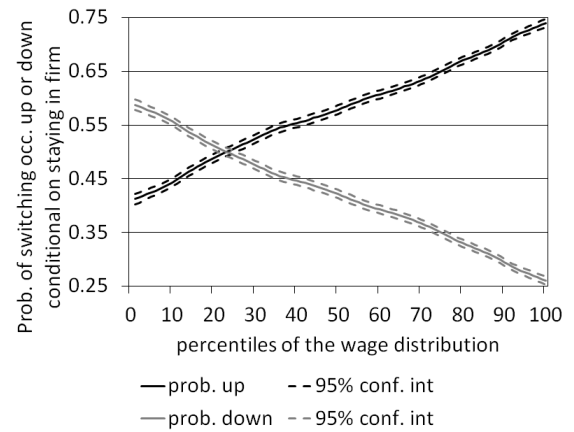
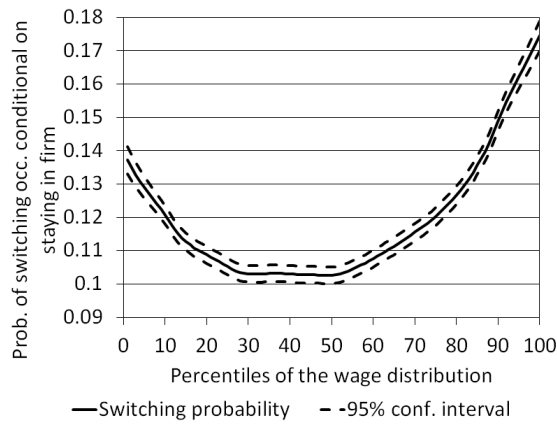


Figure OA-25: Non-parametric plots of probability of switching occupation and of direction of occupational mobility *conditional on staying with the firm* by worker's percentile in the distribution of residual wages. Women.

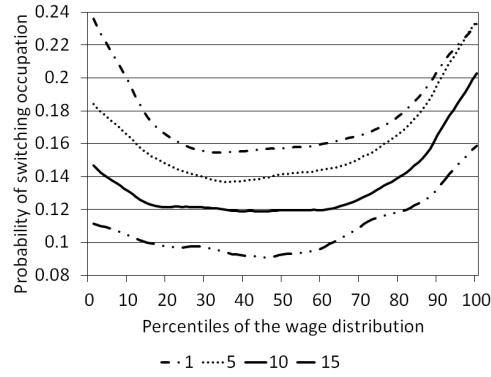
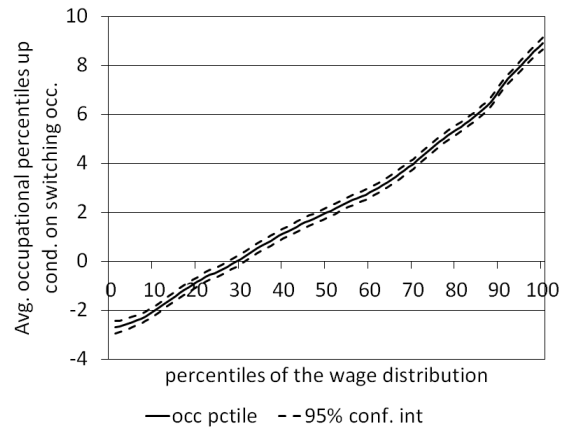


Figure OA-26: Non-parametric plot of probability of switching occupation by worker's percentile in the distribution of raw wages within occupation, year, and experience. Women.



(a) Raw wages.



(b) Wage residuals.

Figure OA-27: Non-parametric plot of direction of occupational mobility in terms of change of occupational percentiles from raw wages or residuals, conditional on switching occupation, by worker's percentile in the distribution of raw wages or wage residuals. Women.



## OA8 Sensitivity to Alternative Occupational Classifications

In this appendix we explore robustness of our findings to a number of alternative ways to define occupations. We begin by considering 1-, 2-, and 3-digit occupational classifications and compare the results to the 4-digit classification used in our main analysis. Figure OA-28 illustrates that our results are robust to using alternative occupational classifications. While the level of mobility falls as occupational classifications become coarser, the U-shaped pattern of mobility remains unaffected. This provides further indication that a considerable part of mobility is driven by movements across occupations that can be vertically ranked which is clearly the case at the 1-digit level.

A potential concern is that some 4-digit occupations may not be sufficiently clearly differentiated (e.g., “Primary education teaching professionals” and “Primary education teaching associate professionals”). This may result in some spurious re-classification of workers’ occupations because of reporting errors or when a worker continues to perform essentially the same task but gets re-classified because of a change in an institutional setting (such as teaching a different grade level). To address this concern we perform the following experiment. We access the Statistics Denmark’s web page that firms can use to search for the correct occupational category of their employees. Typing in a description of the tasks performed by an employee into a search engine provided on this web page, returns one or more 4-digit occupational codes related to the query. For example, if we search for the word “painter,” four distinct 4-digit occupations are returned. These are “Painter and related work,” “Varnisher and related painters,” “Glass, ceramics, and related decorative painters,” and “Sculpture, painters and related artists.” Similarly the search for the word “accountant” or “accounting” returns three 4-digit occupations, which are “Accountants,” “Bookkeepers,” and “Accounting and bookkeeping clerks.” We go through all 4-digit occupations, excluding managers, and search for the word that describes the given occupation (this is done in Danish, of course). We then group together all occupations returned by the search engine. This means that a switch from “Accountant” to “Bookkeeper” or to “Accounting and bookkeeping clerks” will not be registered as an occupational switch. A complete description of the resulting occupational groups can be found in Table OA-1, where Column 2 provides a set of occupations related to the corresponding occupation listed in Column 1 (occupational codes and their descriptions can be found in Appendix OA19). In Figure OA-29(a) we plot the probability of switching across these occupational groups as a function of the worker’s position in the wage distribution of their occupation.<sup>OA1</sup> We find that the U-shaped mobility patterns are robust to

---

<sup>OA1</sup>We keep the wage percentiles from the 4-digit occupations rather than the new defined occupational groups because the groups are not in a “closed relation.” As an example, an “Accountant” is grouped with “Accounting and bookkeeping clerks” who, in turn, are grouped with “Administrative secretaries and related associate professionals.” However, “Accountants” are not grouped with “Administrative secretaries and related associate

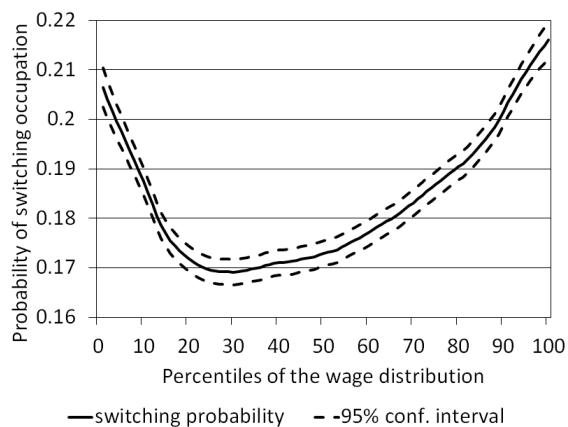
this re-classification of related occupations, while the level of occupational mobility is naturally somewhat lower.

To assess whether our finding that workers with relatively high wages are more likely to leave their occupations is predominantly driven by promotions to managerial occupations we perform the following two experiments. First, we reclassify all managers as one occupation. Second, we exclude all managers from the sample. The results, plotted in Figures OA-29(b) and OA-29(c), respectively, indicate that U-shaped pattern of mobility is not mainly driven by movements in and out of managerial occupations.

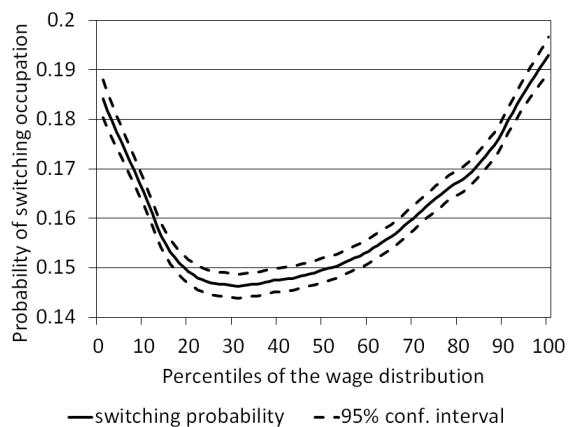
Finally, in Figure OA-29(d) we plot the mobility patterns on the sample that excludes “... not elsewhere classified” occupations (their codes end with the number “9”). The U-shaped mobility patterns are not affected by this change in the sample.

---

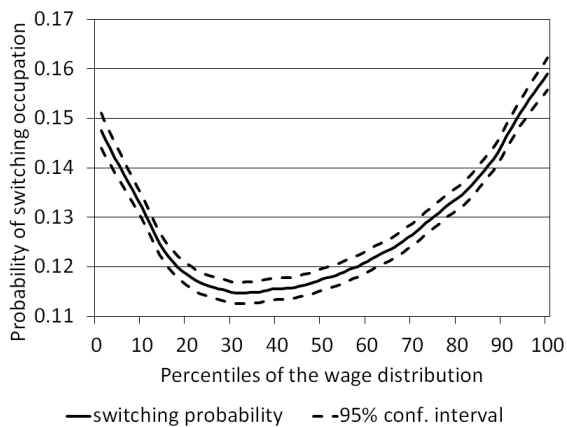
professionals.”



(a) Four-digit classification.



(b) Three-digit classification.

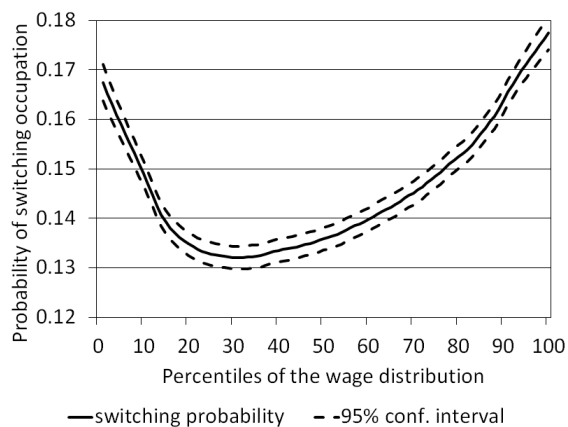


(c) Two-digit classification.

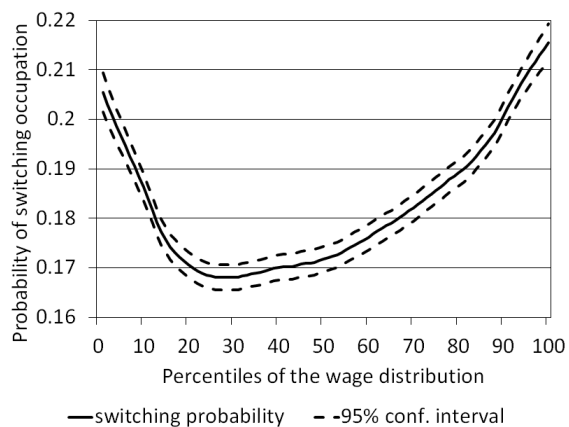


(d) One-digit classification.

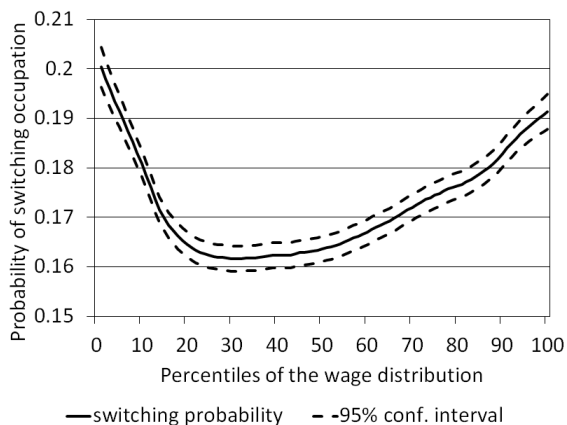
Figure OA-28: Non-parametric plot of probability of switching occupation by worker's percentile in the distribution of raw wages within occupation, year, and number of years after graduation. Various occupational classifications.



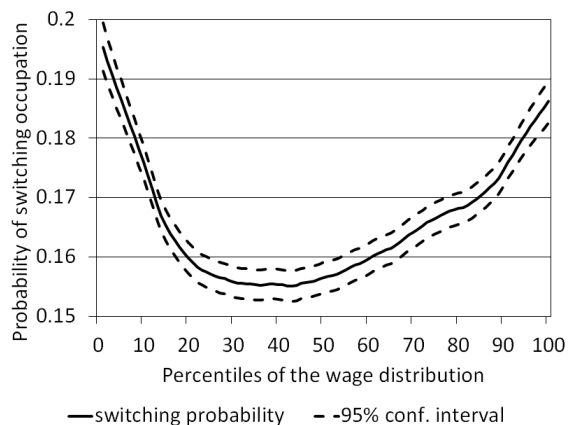
(a) Constructed occupational groups.



(b) All managers in one occupation.



(c) No managers in sample.



(d) No "Not elsewhere classified" occupations.

Figure OA-29: Non-parametric plot of probability of switching occupation by worker's percentile in the distribution of raw wages within occupation, year, and number of years after graduation. Various occupational groupings.

Table OA-1: Grouping of “related” 4-digit occupations

Occupation	Related Occupations
2111	2114, 3111
2113	3119, 3111, 3116, 2146, 3211
2114	8155, 3117
2122	4122, 2411, 4121, 3433, 3413, 3417, 3419, 3412, 3411
2131	2132, 2139, 4113, 7243, 3121, 3122, 3112, 3113, 3114, 3123
2132	2131, 2139, 4113, 7243, 3121, 3122, 3112, 3113, 3114, 3123
2139	2131, 2132, 4113, 7243, 3121, 3122, 3112, 3113, 3114, 3123
2141	3471, 2142, 3112, 2147, 3118
2142	2141, 3112, 3471, 2147, 3118
2143	
2144	3132, 7244
2145	3141
2146	3211, 3116, 3111, 2113, 3119, 2211
2149	3151, 3417, 5161
2211	3211, 2146, 3116, 2113, 3119, 3211
2212	3226, 3228, 2224, 3229
2213	3152, 3212, 6112, 9211, 6141, 2320, 3212, 9212
2224	2212, 3226, 32289, 3229
2229	2224, 2212
2310	
2320	3473, 2454, 2453, 6141, 2213, 3212, 9212, 6112
2331	2352, 2351, 2359, 3310, 3320
2359	2351, 2352, 3310, 2331, 3320
2411	4121, 3433, 3413, 3417, 3419, 3412, 3411, 4122, 2122
2412	2419
2419	2412
2421	2422, 2429, 2470, 3450, 5162
2429	2422, 2421, 2470, 3450, 5162
2432	
2441	
2442	
2443	
2444	
2451	4143
2452	7341
2470	2421, 2422, 2429, 3439, 3432, 3431, 3442, 4115, 4222, 2421, 2422, 2429, 3450, 5162
3111	2113, 3119, 3116, 3211, 2146
3112	2141, 2142, 3471, 2147, 3118
3113	3114, 7242, 8283, 7241, 2131, 2132, 2139, 4113, 7243, 3121, 3122, 7131
3114	3113, 7242, 8283, 7241, 2131, 2132, 2139, 4113, 7243, 3121, 3122, 7131
3115	7311, 8331, 7136
3116	2113, 3111, 3119, 2146
3117	2114, 8155
3118	2141, 3471, 2142, 3112, 2147
3119	2113, 3111, 3116, 4132, 3152, 7224
3121	2131, 2132, 2139, 4113, 7243, 3122, 3112, 3113, 3114, 3123
3122	2131, 2132, 2139, 4113, 7243, 3121, 3112, 3113, 3114, 3123
3123	2131, 2132, 2139, 4113, 7243, 3122, 3112, 3113, 3114, 3121, 8170
3131	7311, 7341, 7343, 7344, 2455, 3139
3132	3144, 7244
3141	2145
3142	8340
3144	
3151	2149, 3417, 5161
3152	2213, 3212, 6112, 9211, 4132, 3119
3211	2146, 3116, 2113, 3119, 3211, 2211
3212	2213, 3152, 6112, 9211, 3213
3213	2212, 3152, 6112, 9211, 3213
3224	4222, 3225, 7311
3310	2331, 3320, 2351, 2352, 2359
3320	2331, 3310, 2351, 2352, 2359
3340	3460, 5132, 3330
3411	2411, 3417, 3419, 3412, 3413, 4121, 3433, 4122, 2122
3415	3419
3416	
3419	2411, 3413, 3417, 3412, 3411, 4121, 3433, 4122, 2122, 3415
3421	3422, 3423, 3429
3422	3421, 3423, 3429, 4133
3429	3421, 3423, 3422
3431	3432, 3439, 3442, 4115, 4222, 2470
3433	2411, 4121, 3411, 3412, 3413, 3417, 3419, 4212, 4211
3434	4121, 4122
3439	3432, 3431, 3442, 4115, 4222, 2470, 2431, 4141
3442	3441, 3431, 3432, 3439, 4115, 4222, 2470
3471	2141, 2142, 3112, 3118

*continued on next page*

Table OA-2: Grouping of “related” 4-digit occupations

*continued from previous page*

4113	2131, 2132, 2139, 7243, 3121, 3122
4114	
4115	3431, 3432, 3439, 3442, 4222, 2470
4121	2411, 3433, 3411, 3412, 3413, 3417, 3419, 2122, 4122, 3431, 3432, 3439, 3442, 2470
4122	2411, 3433, 3411, 3412, 3413, 3417, 3419, 2122, 4121, 3431, 3432, 3439, 3442, 2470
4131	9330, 5220, 4223, 4133, 4131
4132	3119, 3152
4133	3422, 4131, 9330, 5220, 4223
4142	2431, 3439, 8324, 9151, 4141, 9152, 9141, 9330, 8321, 9151
4190	4115, 3431, 3432, 3439, 3442, 4222, 2470
4211	3433, 4212
4212	3433, 4211
4222	3224, 3225, 7311, 4223
4223	3224, 3225, 7311, 4222
5111	
5122	3223, 5121
5123	9132, 9141
5131	5132, 5133, 5139, 3222, 2230, 3221, 3133, 3231, 3340, 3460, 3330, 3443, 2446, 5141, 5149
5132	5131, 5133, 5139, 3222, 2230, 3221, 3133, 3231, 3340, 3460, 3330, 3443, 2446, 5141, 5149
5161	3151, 2149, 3417, 5169, 7216
5169	5161, 3151, 2149, 3417
5220	4223, 4133, 4131, 9330
6112	6130, 6111, 2213, 3212, 9211, 3152
6121	2223, 9211, 6129, 6122, 6130
6129	2223, 9211, 6121, 6122, 6130
6130	6129, 2223, 9211, 6122, 6121, 6112, 6111, 2213, 3212, 3152
6141	2213, 3212, 9212, 6112
6152	6151, 6153
7113	7112, 7111, 8111, 8112
7121	7131
7122	9313, 7123, 3112, 7311, 7312, 7331, 8240, 9320
7123	9313, 7122, 3112, 7311, 7312, 7331, 8240, 9320
7124	9313, 3112, 7422, 7311, 7312, 7331, 8240, 9320
7129	9313, 3112
7131	7121
7132	9313, 3112
7134	9313, 3112
7135	
7136	3112, 3115, 7311, 7223, 7213, 7214, 7222, 7221, 8124
7137	3114, 3113, 7242, 8283, 7241, 2131, 2132, 2139, 4113, 7243, 3121, 3122, 7131, 8283, 8282, 8281
7139	9313
7141	7142, 8223, 9313
7142	7141, 8223, 9313
7143	9313
7211	
7212	7213, 7214, 7215
7213	7212, 7214, 7215
7214	7213, 7212, 7215
7221	7136, 7213, 7214, 7222, 7223
7222	7136, 7213, 7214, 7221, 7223
7223	7136, 7213, 7214, 7222, 7221
7224	3119
7231	7232, 7233
7232	7231, 7233
7233	7231, 7232
7241	7242, 7243, 2131, 3132, 2139, 4113, 3121, 3122, 7241, 3113, 3114
7242	7241, 7243, 2131, 3132, 2139, 4113, 3121, 3122, 7241, 3113, 3114
7243	7242, 7241, 2131, 3132, 2139, 4113, 3121, 3122, 7241, 3113, 3114
7245	8332, 9312
7311	7312, 3115, 8331, 7136, 3224, 3225, 4222
7312	7311, 3115, 8331, 7136, 3224, 3225, 4222
7313	
7331	
7341	2452, 8253, 8251, 7345, 9320
7343	
7344	3131, 7311, 7341, 7343, 2455, 3139
7345	8252
7346	
7411	5220, 8271
7412	8274
7413	8272
7414	
7422	7124, 7311, 7312, 7331, 8240, 9320, 9313, 3112, 9313
7423	8240
7437	7432, 7433, 8261, 8262, 8263, 7434, 7435, 7436, 7431, 7441, 7442
7442	7432, 7433, 8261, 8262, 8263, 7434, 7435, 7436, 7437, 7441, 7431

*continued on next page*

Table OA-3: Grouping of “related” 4-digit occupations

*continued from previous page*


---

8112	7111, 7112, 7113, 8111
8113	
8122	8121, 8123, 8211
8123	8122, 8121, 8211
8124	7136
8131	8139
8139	8131, 7324, 7323, 7322, 7321
8141	8142, 8143, 6141, 8240, 9330
8143	8142, 8141, 6141, 8240, 9330
8151	8212, 8152
8155	2114, 3117
8159	8229
8161	
8162	9311
8170	3132
8211	8121, 8122, 8123
8212	8151, 8152
8221	
8223	7142, 7141, 9313
8229	8259
8231	
8232	
8240	8142, 8143, 6141, 9330
8251	8252, 8253, 7345, 7341, 9320
8252	8251, 8253, 7345, 7341, 9320
8253	8252, 8251, 7345, 7341, 9320
8261	7431, 7432, 7433, 8262, 8263, 7434, 7435, 7436, 7437, 7441, 7442
8262	7431, 7432, 7433, 8261, 8263, 7434, 7435, 7436, 7437, 7441, 7442
8263	7431, 7432, 7433, 8262, 8261, 7434, 7435, 7436, 7437, 7441, 7442
8266	8269
8269	
8271	7411, 3416, 5220
8273	
8274	7412
8275	7414
8278	
8279	7416
8281	8282, 8283, 7137
8282	8281, 8283, 7137
8283	8281, 8282, 7137
8284	
8285	
8286	
8287	
8290	
8322	
8323	
8324	
8331	3115, 7311, 7136
8332	7245, 9312
8333	
8334	
8340	3142
9113	
9132	9131, 5123, 9141
9141	5123, 9132
9142	
9151	8321, 4142
9152	
9161	
9211	2213, 3152, 3212, 6112, 6121, 6129, 6111
9212	8332, 7245
9213	6154
9312	
9313	7122, 7123, 7124, 7121, 7129, 7131, 7132, 7133, 7134, 7135, 7136, 7137, 7139, 7141, 7142, 7143
9320	8251, 8252, 8253, 7345, 7341
9330	5220, 4223, 4133, 4131, 8240, 8142, 8143, 6141

---

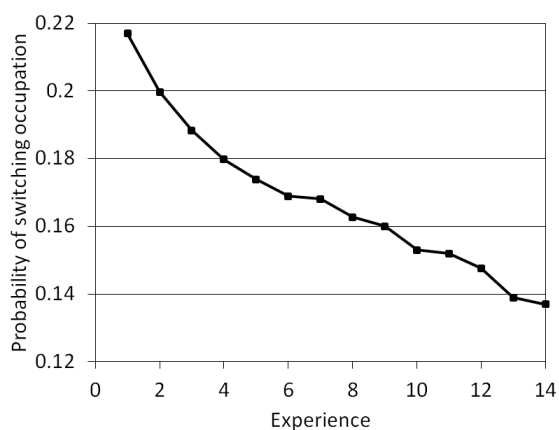
## OA9 Further Discussion on the Effects of Measurement Error

In this Section we provide additional discussion of the possible effects of the measurement error in occupational affiliation data. Since the occupational code is provided to Statistics Denmark by the firm it is more likely for a worker's occupational affiliation to be miscoded when the worker switches firms. However, we have seen that the U-shapes are robust to workers switching occupation *conditional on switching* firms as well as workers switching occupation *conditional on staying* with the same firm. Similarly, the direction of occupational mobility is also unchanged when conditioning on occupation *and* firm switchers or conditioning on occupation but *not* firm switchers. If measurement error were sizable, we would expect switches across firms to be more random and have a flatter curve than switches within firms. We do not find any evidence of this. These results suggest that measurement error is unlikely to substantially affect our findings. Moreover, in Section 2.4.4 we have also seen that grouping occupations together based on the similarity of their descriptions also did not affect our findings, again suggesting only limited possibility for measurement error to play an important role.

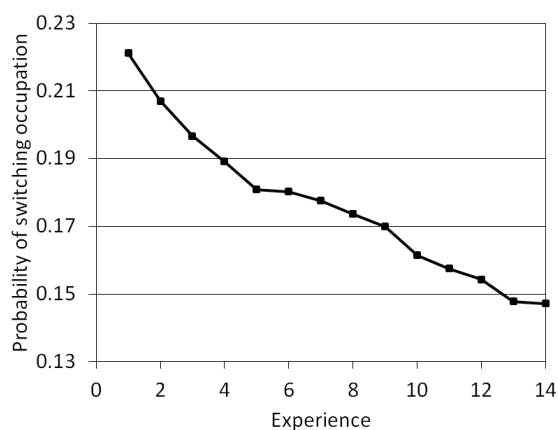


## OA10 Occupational Mobility and Labor Market Experience

Figure OA-30 shows, on the large and small samples, the predicted probability of switching occupation by years of experience, conditional on the observables used in the benchmark wage regression in the main text. The switching probability is estimated with a logit model including each year of experience as a dummy variable and including all other explanatory variables from the wage regression (e.g., education, tenure in firm, industry, and occupation, marital status, time dummies, and lagged regional unemployment rates). The figure implies that occupational mobility declines substantially with age, a pattern widely documented in the other sources of data in the literature.



(a) Small sample

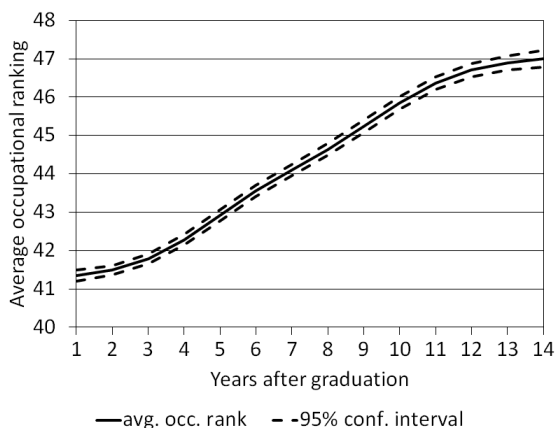


(b) Large sample

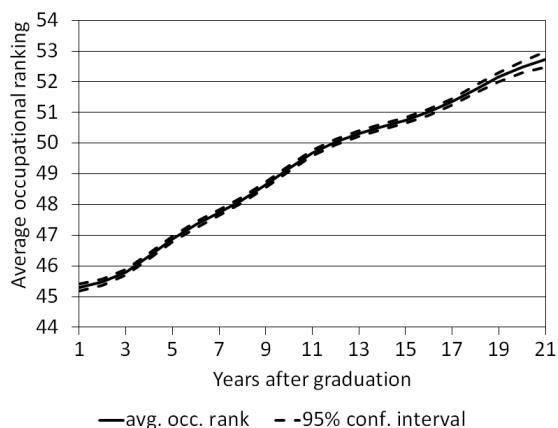
Figure OA-30: Predicted probability of switching occupation by years of experience.

# OA11 Average Occupational Percentile by Labor Market Experience

Figures OA-31 and OA-32 show the average occupational percentile by years after graduation. Similar to the findings in the US literature, reviewed in Footnote OA2 in the online appendix, we find a strong tendency for workers to move up to higher paying occupations with age.

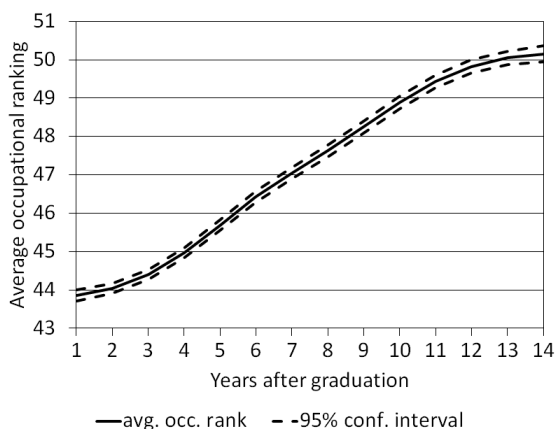


(a) Small sample

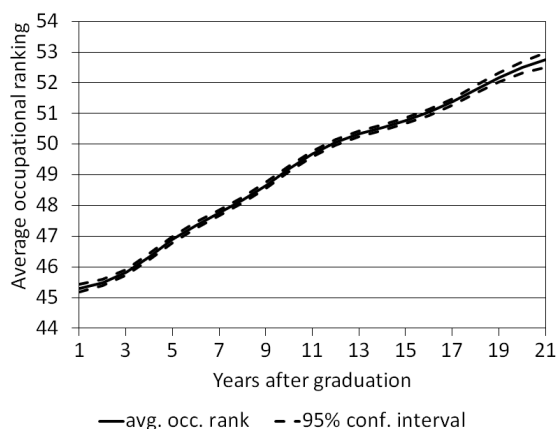


(b) Large sample

Figure OA-31: Average occupational percentile by years after graduation. Occupation percentiles from raw wages.



(a) Small sample

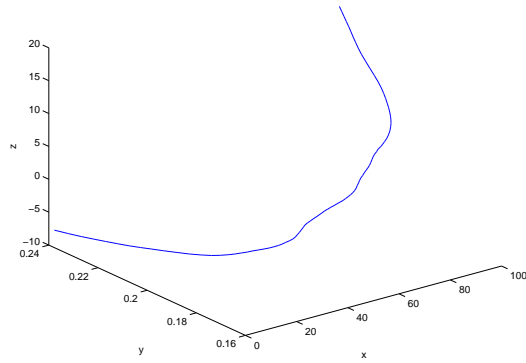


(b) Large sample

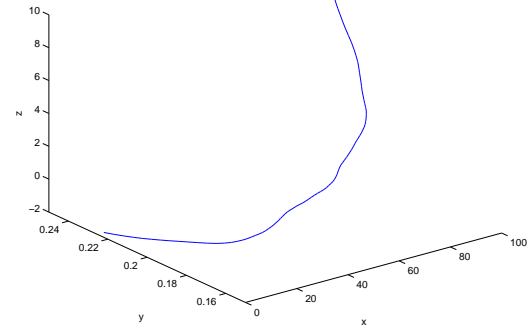
Figure OA-32: Average occupational percentile by years after graduation. Occupation percentiles from wage residuals.

## OA12    Alternative Representation of the Patterns of Occupational Mobility

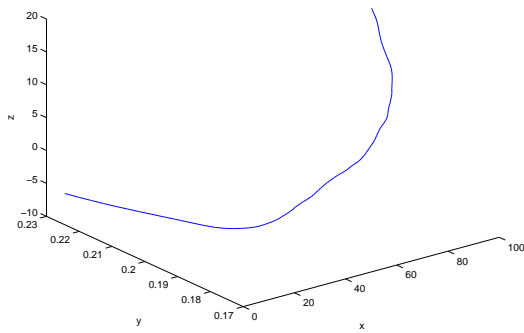
Several key patterns of occupational mobility documented in the main text can be simultaneously summarized in one plot, as in Figure OA-33. The  $x$ -axes measures the percentiles of the within-occupation wage distribution, the  $y$ -axes measures the probability of switching occupation, and the  $z$ -axes measures the average number of occupations a worker moves up (where moving down counts negatively) conditional on the worker switching occupations. While the figure captures all the relevant information in a very concise fashion, it seems relatively difficult to visually interpreted. Instead, in the main text we report the projections of this figure that together provide all the relevant information. In particular, in separate figures we report, for workers at each percentile of the within-occupation wage distribution (1) the probability of changing occupations, (2) the probability that the switch involves a move to a higher ranked occupation, and (3) the average number of ranks moved up (moves down counted negatively).



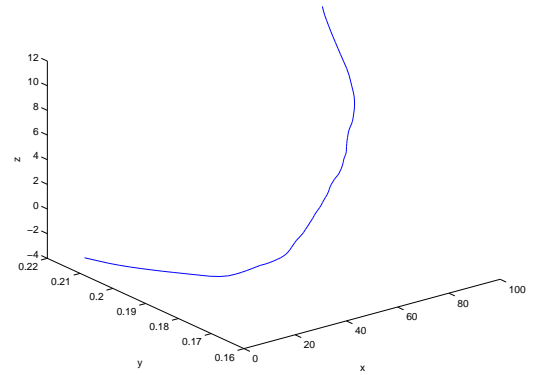
(a) Large sample, raw wages.



(b) Large sample, residual wages.



(c) Small sample, raw wages.

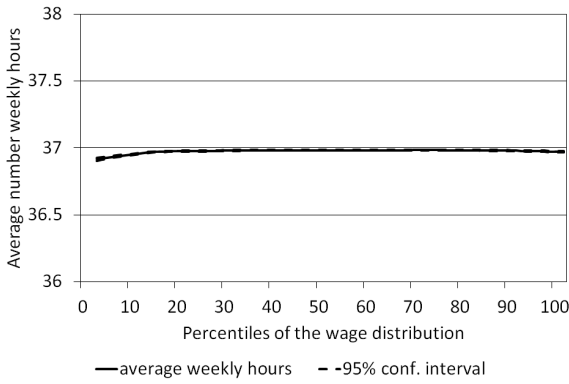


(d) Small sample, residual wages.

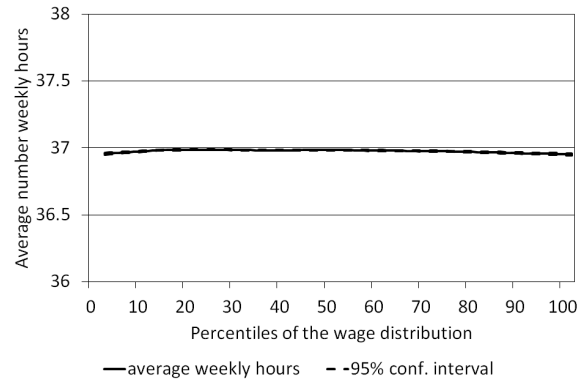
Figure OA-33: Non-parametric plot of probability of switching occupations and of the magnitude of a change in occupational rank upon a switch, conditional on workers' position in the within-occupation wage distribution. Sample of male workers.

## OA13 Average Hours Worked by Percentile of Within-Occupation Wage Distribution

Figure OA-34 plots the average weekly hours worked by workers across percentiles of the within-occupation wage distribution. We find that average hours are relatively constant, although slightly lower for workers with the lowest wages in their occupations.



(a) Distribution of raw wages.



(b) Distribution of wages residuals.

Figure OA-34: Non-parametric plot of average number of weekly hours worked by worker's percentile in the relevant wage distribution.

## OA14 Extensions and Alternative Explanations

As we mentioned, our empirical findings on the shape and the direction of sorting conflict with predictions of match-specific learning models (Jovanovic (1979), McCall (1990), Neal (1999)) and of island-economy models with human capital (Kambourov and Manovskii (2005, 2009a)). In both types of models low wage earners tend to switch, and since they did not receive any additional information about their fit to other occupations they take a random draw for their next occupation. In contrast, the crucial part of our model is that the experience of workers in their current occupation determines their choice of the next occupation, and that the occupations can be ranked. In such a world a bad fit can be characterized by underqualification *or overqualification* of a worker for a particular job. This means that it is not only low wage workers who leave an occupation, but also very qualified workers with high wages. This logic already highlights that it is the vertical sorting part of our theory that is most important. What drives the changes in workers ability is less relevant, even though we believe that learning gives a particularly natural interpretation. In the following we discuss alternative explanations.

### OA14.1 Shocks to Ability

Assume that ability is perfectly observable, but ability changes from one period to the next according to  $a_{i,t} = a_{i,t-1} + \varepsilon_{i,t}$ , where the term  $\varepsilon_{i,t}$  still is drawn i.i.d. from a normal distribution with mean zero and variance  $\phi_\varepsilon$ . It is easy to see that also in this setting workers sort into better occupations after sufficiently positive shocks, and into lower occupations after sufficiently negative shocks, and mobility remains U-shaped. Yet mobility does not decline with labor market experience, in contrast to the case with learning where over time the relevance of additional information declines. If one combines shocks to ability with learning, we conjecture that mobility does decline because of the role of learning but declines less and remains non-trivial even for older workers due to the presence of the shocks to ability.

### OA14.2 Learning-by-Doing, Promotions, and Switching Costs

In our basic model, ability was constant over time. Improvements in general ability through learning-by-doing can be easily incorporated by assuming that ability increases deterministically with years of labor market experience (e.g.,  $a_{i,t} = a_i + \theta t$  for some parameter  $\theta$ ). Since human capital acquisition follows a known and deterministic process, workers can filter it out and learn the same about the fixed but unknown component  $a_i$  as in our basic model. Even though they sometimes revise their assessment about their skills downward after negative output realizations, on average there is a positive drift in their assessment of their skills because they incorporate the deterministic time trend. This leads naturally to a somewhat higher aggregate probability of switching to higher than to lower occupations, as is visible in Figure 3. In Appendix OA11 we show

that indeed the average occupational rank of workers increases with labor market experience.<sup>OA2</sup> Even in the absence of any belief-updating (i.e., even if the variance of the first signal is zero and  $a_i$  is fully observed) the accumulation of general human capital would generate upward mobility in the model. Downward mobility can arise either through belief-updating as in our model, but would also arise if large amounts of skill become obsolete at stochastic points in time.

We should note that general human capital accumulation through learning-by-doing as discussed in the previous paragraph differs from occupation-specific human capital accumulation. In particular, the latter acts as a switching cost since it is lost when changing occupation. While the workers problem now becomes a dynamic program that is harder to analyze, numerical examples suggest that for plausible specifications of general and occupation-specific human capital accumulation the high levels of occupational mobility and the U-shapes persist, as indicated for a particular parametrization in Figure OA-36 in Appendix OA17. It might be worth noting that the wage-distribution within different occupations have overlapping support because of the switching costs, which accords with the substantial overlap in the data but was absent under costless switching when wages are given by (6). Such overlap is always present if wages are at least partially paid according to (5) because in that case wages do reflect actual output and not only the prior about mean ability.

Part of Appendix OA17 lays out a general formulation for human capital accumulation and switching costs, and formalizes the workers dynamic program and the market equilibrium. We think that this is important in future work that tries to control for selection precisely to estimate these aspects of human capital improvements. In Appendix OA18 we show that our structure shares key elements with a more reduced form specification in Gibbons, Katz, Lemieux, and Parent (2005), and therefore inherits the instruments that they employ to control for endogeneous sectoral choice.<sup>OA3</sup> While these are permissible only if there are no shocks to occupational productivity over time, they might constitute a promising first step to assess human capital accumulation in

---

<sup>OA2</sup> Hall and Kasten (1976) and a number of later papers (e.g., Miller (1984), Sichernam and Galor (1990)) have also found that there is a systematic tendency for workers to move up to higher paying occupations with age. Wilk and Sackett (1996) have noted the tendency of workers to move to occupations requiring higher cognitive skills with age. Note that human capital accumulation is not necessary to induce an upward bias in switching: Depending on the precise values of the  $\gamma_k$ 's and  $P_k$ 's the workers might enter mostly in low occupation when young and then move up (or the reverse, depending on parameters). The main effect of general human capital is that it adds an *additional* element that unambiguously shifts young low-human-capital workers to less productive occupations and older high-human-capital workers to more productive occupations.

<sup>OA3</sup>Gibbons, Katz, Lemieux, and Parent (2005) consider the partial equilibrium problem of a worker that faces a similar payoff structure as in our model. They argue which lagged variables can serve as instruments for occupational choice within the structure. They use this on a small dataset and do not check the implications for occupational mobility that our work highlights. Also, their partial equilibrium model has the worker payoffs raised to an exponential power which has the feature that in the absence of human capital accumulation young workers would work in high occupations because the upside potential of their ability within the exponential structure is particularly high. Over time workers on average move to lower occupations in the absence of human capital accumulation. Despite these differences, the main message in terms of applicability of instrumental variables still applies here. We discuss the connections more deeply in Appendix OA18.

the presence of endogeneous selection of the kind highlighted in this paper.

### **OA14.3 Compensating Differentials**

It might be possible to obtain U-shaped switching based on compensating differentials.<sup>OA4</sup> Assume workers do not only differ in their productivity but also in their disutility of working in a particular occupation, and there are switching costs and bargaining within the job. Then workers with high disutility have higher value of leaving the job, and the firm can only entice them to stay by bargaining up to a higher wage. High wage workers would be either very productive or disliking the job, and the latter are more likely to change if an opportunity arises. Similarly, low paid workers might either be unproductive or have low disutility of working in this occupation, and in this case the former would be more inclined to leave the occupation if a new occupation would allow them a new draw of productivity. This could include U-shapes in occupational switching, but does not immediately suggest a particular direction in terms of the new occupation that workers select.

One might also conjecture that high-wage workers are low-hours workers, who turn out to have high wage (earnings divided by hours) because they have low hours. They might move to seek longer hours, even if their wage rate falls, because they want more earnings. We investigate this possibility further in Appendix OA13. In particular, in Figure OA-34 we plot the average weekly hours by percentile of the within-occupation wage distribution. We find that average hours are relatively constant, although slightly lower for workers with the lowest wages in their occupations. The variation in hours appears too small to have a substantial impact on our main findings.

### **OA14.4 Internal Labor Markets within Firms**

In Section 2.4.2 we documented U-shapes in occupational mobility both in the total sample, as well as conditional on staying with the same firm or switching firm. In figure OA-35 we replicated the graphs where wage percentiles are computed from residual wages and added two extra lines of minimum and maximum mobility in the graphs. Despite an overall similarity in pattern, there do remain substantial differences between the graphs. First, the solid lines of Figures OA-35(a), OA-35(b), and OA-35(c) indicate that the average level of occupational mobility is very different, ranging from 18.3% overall to 14.2% for firm-stayers and 34.5% for firm-switchers. Second, there are large differences in the depth of the U-shape given by the difference between the minimum occupational mobility and the maximum occupational mobility (measured as the average mobility of the top 5 percentiles and bottom 5 percentiles of the within-occupation wage distribution). It is 4.0% overall and increases to only 5.0% for firm-switchers even though average mobility is

---

<sup>OA4</sup>We thank an anonymous referee for pointing out this possibility.



roughly doubled. It is 3.0% for firm-stayers. Finally, the U-shape is more skewed to the left on the sample of firm switchers and to the right on the sample of those staying with the firm.<sup>OA5</sup>

It is possible that conditions within a firm are a driver of occupational mobility. That more high-ability workers change occupations within firms might be due to sophisticated contractual and information settings within the firm. For example, if firms use up-or-out contracts and learn workers’ ability before the workers themselves do, they would promote the higher-ability individuals to new tasks and separate from the others. However, the right hand side of the directional graphs OA-12 and OA-13 in these figures are nearly identical, meaning that conditional on ability a worker who switches occupation is not more likely to move to a higher ranked occupation within the firm than across firms. While there might still be a role of within-firm contracts for occupational mobility, this observation led us to abstract from the role of firms in the simplest benchmark version of our model.

An alternative viewpoint is that occupational mobility might affect mobility across firms. We explore this channel here in more detail, and show that our model of frictionless occupational mobility combined with a very simple “theory” of firm switching can quantitatively account for the observed patterns of occupational mobility conditional on switching firm and conditional on staying with the firm without affecting any of the analysis so far in the paper. We retain the overall theory of frictionless mobility and, in addition to our structure on occupations, we envision firms that comprise of many jobs in various but possibly not all occupations. Consider workers who switch employers for random reasons as well as when a change in occupation is desired but the new occupation is not available within the firm (Papageorgiou (2011) proposes a similar logic in a model without occupational hierarchies). In such a setting, the probability of switching occupation conditional on switching employer would be substantially higher than conditional on not switching employer, because some employer changes are precisely motivated by the desire to change occupations, which might explain the level difference between the graphs in Figures OA-35(b) and OA-35(c). To match the observation that conditional on staying within the same firm the U-shapes are more pronounced at the top, while conditional on switching firms they are more pronounced at the bottom, we need the asymmetry that workers tend to find it easier to switch up within the firm than to switch down within the firm. We find this to be the case in the data, although a more elaborate theory of firm-worker matching is required to understand why workers tend to be in firms where there is more scope for upward switching than for downward switching.<sup>OA6</sup>

---

<sup>OA5</sup>These numbers are for U-shapes in wage residuals. Similar patterns are evident for raw wages, and a similar methodology to the one that follows can be applied to those. The case of wage residuals gives a more balanced unconditional U-shape and the different direction of skewedness conditional on staying versus switching firm is more visible, making this a clearer benchmark.

<sup>OA6</sup>One obvious explanation is that there are moderate but strictly positive costs of switching firm and that human capital accumulation induces an upward trend in workers’ ability. In that case, after paying the switching costs, a worker would try to find a new firm with more upside than downside potential relative to his current

In the following, we illustrate that our simple view of firms has the potential to account for the data-patterns that we observe. To be more specific, assume that workers randomly switch firm with probability  $\delta$ . Moreover, if they want to switch occupation, then there is a chance that the new occupation is not available within the same firm, in which case they also have to switch firm. Let  $\gamma$  denote the average probability that this is the case. We will explore the consequence that this is not constant across the wage-spectrum a bit later. In our data, the average probability  $\alpha$  of switching occupation is 18.3%. The average probability  $\beta$  of switching occupation conditional on staying with the same firm is 14.2%. Since

$$\beta = \frac{\text{occ switching \& staying with firm}}{\text{staying with firm}} = \frac{(1 - \delta)\alpha(1 - \gamma)}{(1 - \delta)(1 - \alpha\gamma)}, \quad (\text{OA1})$$

we can back out an implied value for the average chance of not finding the desired occupation within the current firm of  $\gamma = 26.4\%$ . Similarly, the average probability  $\hat{\beta}$  of switching occupation conditional on not staying with the same firm is 34.5%. Since

$$\hat{\beta} = \frac{\text{occ switching \& not staying with firm}}{\text{not staying with firm}} = \frac{\delta\alpha + (1 - \delta)\alpha\gamma}{\delta + (1 - \delta)\alpha\gamma}, \quad (\text{OA2})$$

we can back out an implied value for the firm-switching shock of  $\delta = 16.3\%$ . This means that workers leave their firm on average every six to seven years for reasons orthogonal to our theory of occupational mobility, which seems a plausible magnitude.

While these numbers were computed to rationalize the difference in average occupational mobility between firm-switchers and firm-stayers, we now use them to analyze the implied effect on the depth of the U-shape. For firm-stayers, (OA1) is the relevant equation. For firm-switchers, (OA2) is the relevant equation. Instead of using the population-wide average occupational mobility  $\alpha$  in these formulas, we can use the high mobility at the extremes of the within-occupation wage spectrum or the minimum mobility in the interior of the wage spectrum. Using those numbers instead of the average mobility in (OA1) and (OA2), respectively, we can analyze how much mobility should vary for the subgroups of firm-stayers and firm-switchers across the wage spectrum.

In terms of population-wide numbers, the bottom horizontal line in Figure OA-35(a) indicates a minimum mobility of  $\underline{\alpha} = 16.8\%$  and when we average the mobility at the top and bottom 5 percentiles of the wage distribution, as indicated by the top horizontal line, it shows a mobility of  $\bar{\alpha} = 20.8\%$ , yielding a depth of the U-shape of 4.0%. This should have consequences for the mobility of firm-stayers. If we replace the average occupational mobility  $\alpha$  in formula (OA1) by this minimum mobility  $\underline{\alpha}$  and this average maximum mobility  $\bar{\alpha}$ , respectively, we obtain the following implied values for firm-stayers: a minimum mobility of 13.0% and an average maximum

---

ability since it is more likely that it will develop positively. If the expected ability does decline, the worker might unfortunately fail to find the right occupations within the firm. We leave a full development of this theory for future work.

of 16.2%, implying a reduction of the depth of the U-shape to 3.2%. These numbers are close to the actual numbers for firm-stayers in Figure OA-35(c), where the minimum is 12.9% and the averaged maximum is 15.9%, with a depth of the U-shape of 3.0%.

Similarly, we can consider the implications for firm-switchers by replacing the average  $\alpha$  in (OA2) by  $\underline{\alpha}$  and  $\bar{\alpha}$ , respectively. We obtain the following predictions: a minimum mobility of 32.2% and an averaged maximum mobility of 38.1%. This suggests a depth of the U-shape for firm-switchers of 5.9%, which might be surprising because the level of mobility is nearly 100% larger for firm-switchers relative to the full sample but the depth of the U-shape is only increased by 50%. In the data underlying Figure OA-35(b) we indeed find a U-shape with depth 5.1% for firm-stayers, driven a minimum mobility of 33.0% and an averaged maximum utility of 38.1%. In this sense our “theory” of firm mobility tracks the actual data surprisingly closely.

The calculations in particular track the minimum occupational mobility conditional on firm-staying or switching well. For the maximum, we averaged the mobility on the left and on the right of the wage spectrum. This is clearly a simplification. As mentioned earlier, relative to the overall U-shape in Figure OA-35(a), the U-shape for firm-switchers in Figure OA-35(b) is tilted to the left and the one for firm-stayers in Figure OA-35(c) is tilted to the right. While we do not have any asymmetry in this “theory” so far, the data suggest an interesting interpretation: workers in the top of the occupational wage distribution are more likely to have their new occupation within their current firm than workers at the bottom of the occupational wage distribution.<sup>OA7</sup>

Assume, for illustration, that the workers with wages in the top 5% of their occupation who want to switch occupation have a 10% higher probability of finding the new occupation within their current firm relative to the workers in the bottom 5% of within occupation wage distribution.<sup>OA8</sup> That is, high wage earners within an occupation have a chance  $(1 - \gamma_H)$  of having their new occupation in their current firm that is 1.1 times the chance  $(1 - \gamma_L)$  that low-wage workers face, but they have unchanged average so that  $(\gamma_H + \gamma_L)/2 = \gamma$ . This implies that  $\gamma_L = 29.9\%$  and  $\gamma_H = 22.9\%$ . We can now differentiate the mobility at top wages from the mobility at bottom wages. While both are higher than average, they now differ in magnitude. Mobility at the top end of the wage spectrum is computed using  $(\gamma_H, \bar{\alpha})$  instead of  $(\gamma, \alpha)$ . Mobility at the bottom end is computed using  $(\gamma_L, \underline{\alpha})$ , because for these workers the probability of finding the new occupation within their current firm is lower. For firm-stayers we apply these values in

---

<sup>OA7</sup> Occupational switchers who are within top 5% of the wage distribution in the occupation they left have a 9.2% higher probability that the occupation to which they move is present within their old firm relative to occupational switchers who come from the bottom 5% of the wage distribution in their occupation. One reason why high earners might have an easier time finding the new occupation within their own firm is that most workers are in jobs where more upward mobility is possible within the firm and the top wage earners within an occupation tend to have a higher chance to move upward. We do not have a theory why workers select this way, but one possibility is that there are moderate switching costs and since there is some trend of becoming more able over time the upward mobility is more important, so workers tend to choose to enter firms that allow for more upward than downward mobility. We leave this investigation for future work.

<sup>OA8</sup>This number is in line with that in Footnote OA7.

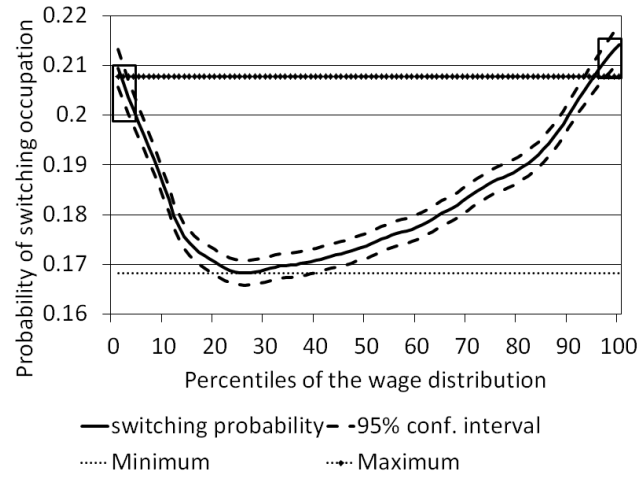
equation (OA1), which yields differences in occupational mobility between the top and the bottom earners of +1.3% (16.8% at the top and 15.5% at the bottom). In the data for firm-stayers the difference is +2.1% (16.9% at the top and 14.8% at the bottom). The occupational mobility of firm-switchers is given by (OA2), and we obtain a difference of -3.6% of mobility between the top and bottom earners (36.3% at the top and 49.9% at the bottom). In the data it is -2.2% (36.9% at the top and 38.1% at the bottom). The fact that we overshoot for firm-switchers means that even for somewhat lower values of  $\gamma_L - \gamma_H$  we would do well on this margin. While this exercise does not match the data perfectly, it tracks it rather closely, suggesting that future work along this lines might hold promise.

We view these findings as an indication that firms can be integrated into our study of occupational mobility in a way that retains the basic insights on occupational mobility but with additional insights on firm mobility. We do acknowledge, though, that a more careful study of the role of firms is necessary. One might conjecture that firms themselves have types and workers sort across firms in a similar manner as they sort across occupations. This might ultimately yield a unifying theory of occupation-firm-worker matches, but it exceeds the scope of this paper. Abstracting from occupations, this path has been pursued in the recent literature that confronts matched employer-employee data.<sup>OA9</sup> Our choice to focus instead on occupational mobility was driven by the large mobility on this dimension and by the large reduced-form estimates on human-capital regressions associated with occupational tenure that seems to require an adequate model to control for selection.<sup>OA10</sup> Since the same regressions do not give the same prominence to firm or industry tenure, since many of the qualitative features are similar for firm-stayers and firm-switchers, and since this section suggests that a simple notion of firms has the potential to explain many features of the data without changing the conclusions on occupational mobility, we concentrated on occupational mobility while abstracting from firm mobility for the main analysis in the paper.

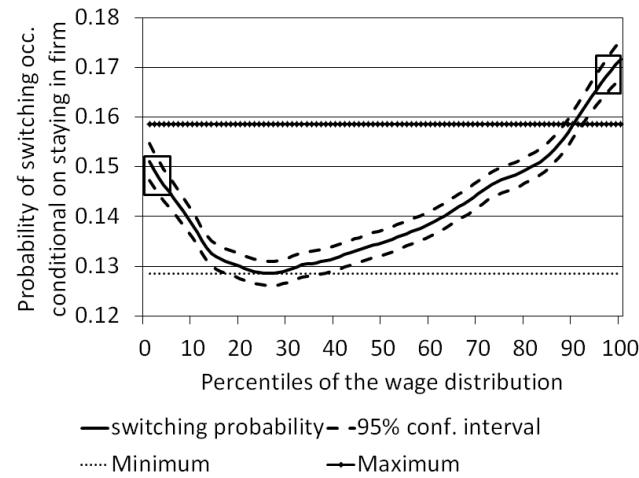
---

<sup>OA9</sup>Starting with the work of Abowd, Kramarz, and Margolis (1999) on two-sided fixed-effect estimation in matched employer-employee data, the firm-worker matching has received increasing attention. Amongst others, Gautier and Teulings (2006), Lopes de Melo (2009), Eeckhout and Kircher (2011), Hagedorn, Law, and Manovskii (2012) provide further literature review, discussion of the structural problems with the fixed-effects estimation, and suggest potential solutions. The concerns carry over to occupation-worker matches, which is one reason why we take a very different empirical path in our analysis. Our approach side-steps these issues, but requires a lot of workers per occupation, which is the reason why we have not used it for the study of firm-worker-matches as we point out in Section 2.4.6.

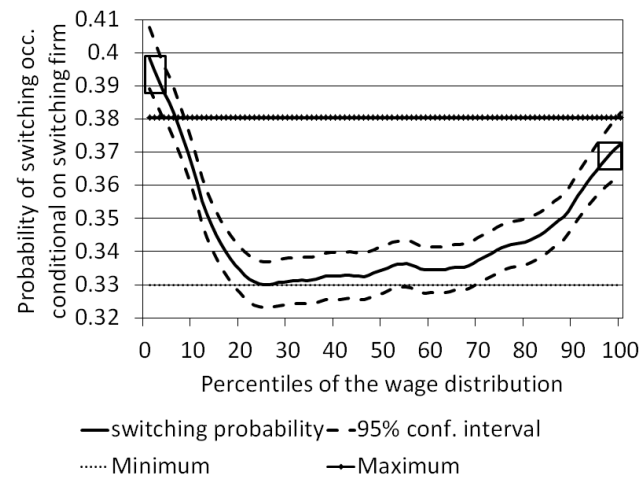
<sup>OA10</sup>For the human-capital analysis, see e.g., Shaw (1984, 1987), Kambourov and Manovskii (2009b), and Groes (2010).



(a) Occupational mobility



(b) Occupational mobility conditional on switching firm



(c) Occupational mobility conditional on staying in firm

Figure OA-35: Non-parametric plots of probability of switching occupation, unconditional, and conditional on switching and staying in the firm. Occupation percentiles from wage residuals.

## OA15 Mobility in Response to Changing Occupational Productivity: Theory

In our study of changing occupational mobility in the main body of the paper, only one occupation changed its productivity. Here we allow simultaneous changes in productivity and show that the main result generalizes. To show this, we need to slightly expand the notation. Denote calendar time by  $\tau$  and index occupations by a name  $r \in \{0, 1, \dots, K\}$  instead of their rank in terms of productivity (since the rank is now changing), with  $r = 0$  still being home production with constant productivity of zero. We retain the same notation as in the main text, with the adjustment for the name of the occupation and an additional superscript indicating calendar time. For example,  $P_r^\tau > 0$  denotes the productivity of occupation  $r$  at calendar time  $\tau$ . Productivities can be deterministic functions of calendar time, but are also allowed to be realizations of some stochastic process. Stochasticity does not affect the analysis since workers can still costlessly change occupations each period. Importantly, the cross-sectional distribution  $F$  of beliefs remains unchanged because it does not rely on occupational choice. Therefore, the model can still be solved period by period. We assume that each period productivities can be strictly ordered.

We also continue to assume that the measure  $\gamma_r$  of entrepreneurs in each occupation  $r$  remains constant, although our results are robust as long as entry is sufficiently inelastic to induce competition among workers for scarce jobs.<sup>OA11</sup> Inelastic labor demand might arise, for example, because a job in an occupation needs a particular type of physical capital that is not easily adjusted when the demand for the services of the occupation changes. See the further discussion in Appendix OA16.

Given the productivities that prevail in period  $\tau$ , let  $\underline{B}_r^\tau$  and  $\overline{B}_r^\tau$  be the lower and upper bounds on the ability (analogous to bounds  $B_k$  and  $B_{k+1}$  in the preceding section). That means that workers with beliefs in  $[\underline{B}_r^\tau, \overline{B}_r^\tau]$  choose to work in occupation  $r$ . Equation (8) readily reveals that these beliefs depend exclusively on the number of jobs that offer lower wages, not on the level of productivity per se. It will therefore be convenient to define  $\Gamma_r^\tau$  as the measure of all jobs that have weakly lower productivity than the jobs in occupation  $r$  in period  $\tau$ . We call  $\Gamma_r^\tau$  the *position* of occupation  $r$  in the distribution of productivities. When the position of a specific occupation  $r$  stays constant for two periods, i.e.  $\Gamma_r^\tau = \Gamma_r^{\tau+1}$ , it follows immediately that the cutoffs that determine who stays in the occupation remain constant, i.e.  $\underline{B}_r^\tau = \underline{B}_r^{\tau+1}$  and  $\overline{B}_r^\tau = \overline{B}_r^{\tau+1}$ , and the switching behavior of workers in occupation  $r$  remains essentially unchanged compared to the baseline model analyzed in the main text.<sup>OA12</sup> Switching is maximal at both ends of the earnings

<sup>OA11</sup>We discuss entry in Appendix OA16. When entry is completely elastic, the model resembles the Roy (1951) model, since each worker essentially decides by himself whether to “buy” a job in occupation  $k$ , independent of the choices of all other workers.

<sup>OA12</sup>For the baseline model in Section 3 where productivities do not change, define  $\hat{s}_{k,t}(X) = s_{k,t}(P_k X - \Pi_k)$  and  $\hat{S}_{k,t}(A) = S_{k,t}(P_k A - \Pi_k)$ . This gives the switching probabilities based on output/ability rather than on the wages.

(and ability) spectrum, and is lowest at intermediate income levels.

When an occupation improves in rank between period  $\tau$  and  $\tau+1$  in the sense that  $\Gamma_r^{\tau+1} > \Gamma_r^\tau$ , the bounds on ability improve in the sense that  $\underline{B}_{r_\tau(k)}^{\tau+1} > \underline{B}_{r_\tau(k)}^\tau$  and  $\overline{B}_{r_\tau(k)}^{\tau+1} > \overline{B}_{r_\tau(k)}^\tau$ . An immediate implication of the increased bounds is that workers who stay in the occupation between the two periods are a positive selection of the initial workforce.

Another implication of the increased bounds of an improving occupation is that high ability workers join while low ability workers are driven out. This has direct consequence of the patterns of switching that we observe. In particular, in rising occupations high wage workers tend to stay while low wage workers tend to leave. The following proposition is proved for the case where firms absorb the uncertainty of the production process.

**Proposition OA 1** *Consider an occupation  $r$  with a sufficient relative rise in productivity such that  $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r$ . If wages are set according to (6), the probability of switching out of occupation  $r$  between  $\tau$  and  $\tau+1$  decreases with higher wages for workers in the same cohort. The reverse holds for a sufficient decline in relative productivity such that  $\Gamma_r^{\tau+1} \leq \Gamma_r^\tau - \gamma_r$ .*

**Proof.** We prove the result for a rising occupation; analogous steps establish the result for a declining occupation. Wages in (6) rise in the prior  $A$ , and the distance  $|\underline{B}_r^{\tau+1} - A|$  decreases in  $A$  for all workers that choose occupation  $r$  in period  $\tau$  [since  $A \leq \overline{B}_r^\tau$  and  $\overline{B}_r^\tau \leq \underline{B}_r^{\tau+1}$  when  $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r$ ]. Thus, workers with a higher prior are closer to the region  $[\underline{B}_r^{\tau+1}, \underline{B}_r^{\tau+1})$  where they stay in  $r$ , and therefore it is more likely that their posterior falls into this region (which follows formally from single-peakedness and lateral adjustment of the update  $G_t$ ). ■

A proposition with similar content can be proved when workers are residual claimants:

**Proposition OA 2** *Consider wages according to (5). Consider an occupation  $r$  that rises sufficiently in position,  $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r$ , and consider the probability of staying in  $r$  between  $\tau$  and  $\tau+1$ . Then only workers who had wages above the occupational mean in  $\tau$  stay, while all lower wage workers leave. The reverse holds for a sufficient decline in position,  $\Gamma_r^{\tau+1} \leq \Gamma_r^\tau - \gamma_r$ .*

**Proof.** Consider the case where  $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r$ ; results for the other case follow analogous steps. Because of the increase in rank, we have  $\underline{B}_r^{\tau+1} > \overline{B}_r^\tau$ , which means that workers only stay in occupation  $r$  if their update exceeds the top threshold before the productivity change. It is easy to see that any worker with mean ability in  $A \in [\underline{B}_r^\tau, \overline{B}_r^\tau)$  that earns a wage at or below the occupational mean has an update  $A' \leq \overline{B}_r^\tau$ . While he could still be suitable for occupation  $r$  if its rank had not changed, he is no longer suitable given that the occupation has improved and better workers compete for the same jobs. ■

---

It can be shown that  $\hat{s}_{k,t}(X)$  and  $\hat{S}_{k,t}(A)$  are invariant to the exact productivity level of occupation  $k$ , as long as it retains the same position among the occupations.

## OA16 Free Entry into Occupations

In the main body of the paper we have taken the number of jobs per occupation as fixed. Here we briefly outline that the model extends to an economy in which jobs can be created at some opportunity cost. Clearly entry costs have to differ between occupations to sustain several occupations with different productivities (since otherwise only the most productive occupations will operate). Assume that the per-period cost to create and maintain a job in occupation  $k$  (or  $r$ , if we adopt the notation from section OA15) is given by  $C_k(\gamma_k) = \bar{c}_k + c(\gamma_k)$ , except for home production sector  $k = 0$  where entry costs are  $C_0(\gamma_0) = 0$ . That is, there is a fixed cost  $\bar{c}_k$  independent of the number of other entrepreneurs who create jobs, and a component  $c(\gamma_k)$  that depends on the overall number of entrants into the occupation.

If we assume that  $c(\gamma_k) = 0$ , then we have perfectly elastic supply of jobs. This corresponds to a model in which workers can simply rent jobs at cost  $\bar{c}_k$ . Occupations with lower productivity have to have lower costs as otherwise no worker would rent the job. The model is particularly simple to solve because firms profits are exogenously tied to the entry costs:

$$\Pi_k = \bar{c}_k. \tag{OA3}$$

This entry assumption corresponds to the standard Roy models which are essentially decision-theoretic: any worker that wants to enter occupation  $k$  can do so by “buying” a machine at cost  $c_k$ , there are no further congestion effects, and competition between workers is essentially absent.

The drawback of having only fixed costs  $\bar{c}_k$  is the response of the market when productivities change over time, as we analyzed for the basic model in Section 4. In a model with absolute advantage, if an occupation becomes more productive than another one but retains its lower entry cost, then the other occupation completely disappears. There are various reasons why we don’t expect this to occur: Prices might change in response to output changes or costs might change in response to the number of jobs in the occupation. Costs change for example if there is heterogeneity among entrepreneurs and  $c(\gamma_k)$  reflects the costs of the marginal entrant: the more entrepreneurs enter the less able the marginal one is.<sup>OA13</sup> We integrate this idea into the model by assuming that  $c(\cdot)$  is increasing and convex. If prices are always high enough to cover the fixed cost, then Inada conditions on the second component ensure that even with changing productivities no occupation completely vanishes, but the level of operation might substantially

---

<sup>OA13</sup>In this interpretation all infra-marginal entrants will generate profits larger than their costs. Only the marginal entrant will be exactly indifferent to entering.



vary.<sup>OA14,OA15</sup> In the limit where it is zero up to  $\gamma_k$  and infinite thereafter corresponds exactly to the setting in the main body of the paper. Here we see that even for intermediate ranges our results carry over when occupations change rank.

An equilibrium is now a tuple  $\Pi = (\Pi_0, \dots, \Pi_K)$  of profits and a tuple  $\gamma = (\gamma_0, \dots, \gamma_K)$  of entry levels such that all conditions in Equilibrium Definition 1 are satisfied and additionally it holds that  $\Pi_k = C(\gamma_k)$  for all  $k > 0$ . All results regarding switching behavior from Section 3 apply, only that now the cutoffs  $B_k$  are determined in a way that incorporates optimal entry. It is easy to solve for these cutoffs by considering the following set of equations in analogy to (7) and (8)

$$\frac{C(\gamma_k) - C(\gamma_{k-1})}{P_k - P_{k-1}} = B_k, \quad (\text{OA4})$$

$$F(B_k) - F(B_{k-1}) = \gamma_k, \quad (\text{OA5})$$

for all  $k > 0$ .

Equation system (OA4) and (OA5) allows us to determine the size of each occupation in each period even in the case when productivities are changing as in Section 4. We can now define an improving occupation in the sense of Proposition 5 as one that improves its position at both the high and the low end, i.e.  $\Gamma_r^{\tau+1} > \Gamma_r^\tau$  and  $\Gamma_r^{\tau+1} - \gamma_r^{\tau+1} > \Gamma_r^\tau - \gamma_r^\tau$ , where again superscripts indicate the time period. A sufficient increase additionally means  $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r^\tau$ . With these extended definitions the proposition remains valid. If on the other hand an occupation with increasing productivity expands so much in size that the measure of jobs with strictly lower productivities  $\Gamma_r - \gamma_r$  actually decreases, it starts to employ not only more high ability but also more low ability workers. When we consider a smooth increase in the productivity of occupation  $r$  and hold the other productivities fixed, it is easy to see that the expansion of the workforce is continuous but the position switches upward when it overtakes another occupation, at which point indeed both upper and lower position  $\Gamma_r$  and  $\Gamma_r - \gamma_r$  increase jointly and the ability of the work force improves substantially in the sense of first order stochastic dominance.

---

<sup>OA14</sup>In particular, it is easy to verify that the following conditions ensure employment in all occupations  $k > 0$  in all periods. Assume that  $c'(0) = 0$  and there is some constant  $\psi > 0$  and employment level  $e = [\alpha T - F(\psi)]/K$  such that  $\lim_{\gamma \rightarrow e} c'(\gamma) = \infty$ , which ensures that no occupation employs more than  $e$  workers. Moreover, assume that prices evolve according to some (possibly stochastic) process with the feature that there exists a lowest price  $P > 0$ . That is, no occupation  $k > 0$  ever draws a price below  $P$ . Then  $\psi P > \max_k \bar{c}_k$  ensures that it is optimal to have at least some employment in each occupation at each point in time because the worker with ability  $\psi$  never gets employed and therefore could be hired for free.

<sup>OA15</sup>Another alternative formulation that ensures the operation of all occupations is that prices are changing while entry costs remain constant, i.e.  $P_k(\gamma_k)$  is dependent on the level of employment and  $C_k$  is fixed. Together with some Inada conditions still all occupation remain active, but the requirement that  $\Pi_k = C_k$  implies that the equilibrium ordering of the productivities  $P_k(\gamma_k)$  of occupations cannot change.

## OA17 Human Capital and Switching Costs

In this setting we allow for a general process of general and occupation-specific human capital accumulation and for switching costs. We introduce these elements into the basic environment of Section 3, and then show in simulations that the basic patterns for mobility still arise for reasonable parameter values.

For general human capital, assume that a worker at the beginning of his  $t^{\text{th}}$  year in the labor market has human capital  $H(t)$ . In the main body of the paper we only considered  $H(t) = \theta t$ , but we allow for a more general specification here. Moreover, a worker who starts his  $\iota^{\text{th}}$  consecutive year in occupation  $k$  has human capital  $h_k(\iota)$ . We normalize both forms of human capital to be zero in the first year, and assume that the human capital functions are weakly increasing. If a worker switches occupation, he loses his occupation-specific human capital and has tenure  $\iota = 1$  in his new occupation. This introduces switching costs, and thus the optimal decisions have to be calculated from a dynamic program that trades off the future gains from switching with the immediate costs. For completeness, we also allow other switching costs  $\kappa_k$  that may arise when a worker switches from occupation  $k$  to a different occupation, which might capture application effort, retraining costs, etc.

Consider a worker with  $t$  years of general labor market experience and  $\iota$  years of occupational experience in occupation  $k$ . There are various ways in which human capital can influence the output process. Our preferred specification is in analogy to (2)

$$X_k = a_i + H(t) + h_k(\iota) + \varepsilon_i. \quad (\text{OA6})$$

leading to expected wage

$$W_k(A) = P_k(A_t + H(t) + h_k(\iota)) - \Pi_k. \quad (\text{OA7})$$

Since human capital accumulation is deterministic, a worker who observes his output can back out  $a_i + \varepsilon_i$ , and therefore learning is not affected by human capital accumulation and the distribution  $F$  of beliefs in the population remains unchanged.<sup>OA16</sup> For this adjusted output process (OA6) the wages are still determined by (5) given the profit  $\Pi_k$  that firms want to obtain. The main difference to the preceding analysis is that workers solve a dynamic programming problem when deciding on the optimal occupation decision. We again consider a stationary equilibrium where firms' equilibrium profits  $\Pi_k$  remain constant over time.

---

<sup>OA16</sup>Alternatively, we could e.g. exponentiate the right hand side of (OA6), which would still leave beliefs in the cross-section unchanged.

As an aside, note that we can add some additional terms  $\alpha H(t)$  with  $\alpha \geq 0$  to (OA7) to account for general human capital that increases the productivity in all occupations but does not interact with productivity of the occupation. This makes it possible to fit a wider range of wage growth patterns. In particular, this type of human capital does not affect sorting and does not induce a drift toward the more productive occupations.

Specifically, for any given profit vector  $\Pi = (\Pi_0, \dots, \Pi_K)$  the worker can forecast his expected wage in all occupations for given prior and given experience. He can then evaluate his optimal choice of occupation by simple backward induction. His state vector at the beginning of each period is  $(t, k, \iota, A)$ : his year in the labor market  $t$ , the occupation  $k$  he was last employed in, his consecutive years of experience in this occupation  $\iota$ , and his belief about his mean ability  $A$ . New entrants start with home production as their previous occupation. In the last year of his life the worker optimizes

$$V(T, k, \iota, A) = \max \left\{ W_k(A, T, \iota), \max_{m \neq k} \{W_m(A, T, 1) - \kappa_m\} \right\},$$

i.e. he chooses whether to stay in his previous occupation or to switch to a new occupation where this would be his first year of experience and pay the switching costs. This gives a decision rule  $d(T, k, \iota, A|\Pi) \in \{0, \dots, K\}$  regarding the occupation that the worker chooses given the profits that firms make. Similarly, a worker with  $t < T$  years of experience maximizes his expected payoff including the continuation value

$$V(t, k, \iota, A) = \max \left\{ \begin{array}{l} W_k(A, t, \iota) + \beta E_{A'} V(t+1, k, \iota+1, A'), \\ \max_{m \neq k} \{W_m(A, t, 1) - \kappa_m + \beta E_{A'} V(t+1, m, 2, A')\} \end{array} \right\},$$

where  $\beta \in (0, 1]$  is the discount factor and  $A'$  is the update about the worker's mean ability. The solution to this problem gives again a decision rule  $d(t, k, \iota, A|\Pi) \in \{0, \dots, K\}$ . It is straightforward to show that for given profit vector  $\Pi$  these decision rules are unique for almost all ability levels  $A$ . Given the distribution  $F_t(A)$  of priors of each cohort and these decision rules, one can derive for given  $\Pi$  the steady-state number of agents that choose occupation  $k$ , call it  $v_k(\Pi)$ . Similar to Equilibrium Definition 1 we can now define:

**Definition OA 1** *An equilibrium is a vector of profits  $(\Pi_0, \dots, \Pi_K)$  such that  $\Pi_0 = 0$  and  $v_k(\Pi) = \gamma_k$  for all  $k > 0$ .*

Consider first the implication of general human capital accumulation ( $H(t)$  strictly increasing) for occupational switching, abstracting from switching costs ( $h_k(\iota) = 0, \kappa = 0$ ). Compared to a world without human capital the distribution of worker productivity now shifts by  $H(t)$  for workers with  $t$  years of experience, since the relevant measure of a worker's ability in producing output is  $a_i + H(t)$ . Even though the new labor market entrants have the same distribution of ability as in the setting without human capital, with general human capital older workers become more productive and induce tougher competition for jobs in more productive occupations. Therefore, young workers start lower and in expectation move up to better occupations over the lifetime. Human capital induces a drift toward more productive occupations, creating another force for the upward movement through the occupation ladder beyond learning.

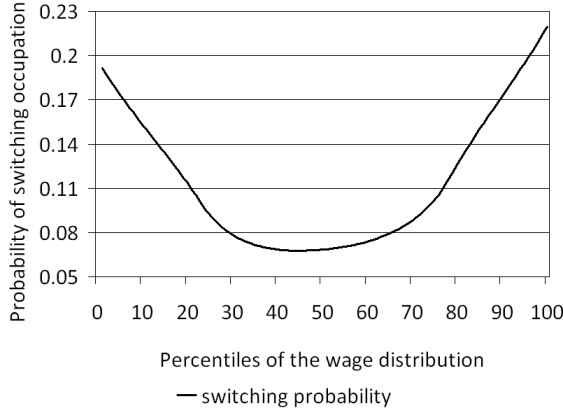
Our insights on U-shapes carry over to the setting with switching costs ( $h_k(\iota)$  increasing,  $\kappa > 0$ ). U-shapes still obtain for any wage setting that is weighted average (5) and (6) with positive weight on (5). In this case wages partially reflect the new information obtained through the realized output, and very high (low) outlier wages can only arise because of very high (low) output realizations, in which case the agent learned that he is much better (worse) than he expected and it can be shown that at the extreme wages the update must be so large that the gains from switching outweigh any finite switching costs. In contrast, when workers are fully insured against the output risk by receiving the expected wage according to (6), the current period wage does not reveal any information about what the worker learned in the current period and the logic of the preceding argument does not apply. In this case, it could be that U-shapes do not arise. This could happen, for example, if older workers are more productive and therefore earn higher wages, but face higher switching costs and therefore have low probability of leaving the occupation.

However, in numerical simulations we always found U-shapes for reasonable parameter values. For instance, consider the following numerical example. We set the model period to be one year and assume that workers are in the labor market for 40 years. We assume that there are 25 occupations (plus home production) of approximately equal size with prices given by  $P_k = 1 + 0.05k$  for  $k \geq 1$ . We set  $H(t) = 0.008t$  and  $h_k(\iota) = 0.008\iota$  for  $\iota \leq 5$  and  $h_k(\iota) = 0.04$  otherwise. These choices imply that during the first 5 years in an occupation wages grow by 10% and half of this wage growth is due to accumulation of occupation-specific human capital and half due to accumulation of general human capital. To ensure that (nearly) all workers have positive ability we normalize average ability to a sufficiently high value  $\mu_a = 50$ . Finally, we set the precision  $\phi_a = 0.667$  and  $\phi_\varepsilon = 0.052$ . At these parameter values the model generates the occupational mobility rate of approximately 10% and the variance of log wages of 0.15. Taken together, sorting and human capital accumulation account for a life-time wage growth of 60%.

Figure OA-36 describes the patterns of occupational switching estimated in the model-generated data. The probability of switching is clearly U-shaped in the position of a worker in wage distribution in his occupation. Moreover, this pattern is also apparent when we condition on years of labor market experience. We emphasize that this is just a numerical example and not an attempt to calibrate the model. However, it is representative of the patterns we observe in simulations for various parameterizations under wage setting given by (6).

## OA18 Relation to Gibbons, Katz, Lemieux, and Parent (2005)

Our model of learning is related to work by Gibbons, Katz, Lemieux, and Parent (2005). They also extend the Roy (1951) model to allow for learning about workers' abilities. They do not



(a) Overall.



(b) For different years after graduation.

Figure OA-36: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution within occupation, year, and years after graduation. Model Simulations.

use an equilibrium model, and do not explicitly analyze the switching behavior of workers as a function of their earnings. Rather, their focus is on the decision-theoretic problem of an individual worker, for which they propose a instrumental variables method based on lagged occupational choices in order to estimate his choice parameters consistently. Since adaptations of their model allow to back out underlying parameters such as productivities or human capital accumulation even in our model (as long as there are not shocks to occupational productivities), it is important to review the connection.

Consider the expected wages in our model, and assume that productivities are constant over time. Therefore, the profit vector  $(\Pi_0, \Pi_1, \dots, \Pi_K)$  remains constant over time. This vector implies that a worker at the beginning of his  $t^{\text{th}}$  period in the labor market who observed output realizations  $(X_0, X_1, \dots, X_{t-1})$  obtains an expected wage according to (6) of

$$E[P_k(a_i + \varepsilon_{it}) - \Pi_k | X_0, X_1, \dots, X_{t-1}] = P_k A_{it} - \Pi_k,$$

where we left out the additive human capital terms for notational convenience. For the decision-theoretic problem of individual worker, profits  $\Pi_k$  can be interpreted as parameters.

Now consider the following transformation where we raise the wage of workers into the exponent:

$$E[e^{\{P_k(a_i + \varepsilon_{it}) - \Pi_k\}} | X_0, X_1, \dots, X_{t-1}]. \quad (\text{OA8})$$

In this alternative process output can be viewed as  $e^{P_k(a_i + \varepsilon_{it})}$ , and profits are a fraction of output. The latter part is harder to interpret in a standard equilibrium setting, but nevertheless this specification gives rise to similar switching patterns, as we will see now. It corresponds to the specification in Gibbons, Katz, Lemieux, and Parent (2005), (who also have additional additive

terms in the exponent capturing occupational and overall tenure and other observed characteristics of the worker). Expression (OA8) is equal to

$$e^{\{P_k A_{it} + (1/2)P_k^2 \phi_t^{-2} - \Pi_k\}}.$$

Workers sort themselves to the occupation with the highest expected wage. Since the ranking of wages is preserved under monotone transformations, we can take logarithms and obtain the sorting criterium:

$$P_k A_{it} - \Omega_{kt},$$

where  $\Omega_{kt} := \Pi_k + (1/2)P_k^2 \phi_t^{-2}$  now reflects the opportunity cost of obtaining the revenue  $P_k A_{it}$  in occupation  $k$ , in contrast to only  $\Pi_k$  in our model. This is due to the fact that the upside potential of uncertainty is larger than the downside potential after exponentiating. This makes young employees especially attractive, as their uncertainty is higher. To see this formally, note that a worker will choose occupation  $k$  if his belief satisfies  $A_{i,t} \in [B_{k,t}, B_{k+1,t})$  where the cutoffs  $B_{kt} = \Omega_{kt} - \Omega_{k-1,t} / (P_k - P_{k-1})$ . This still has the potential to generate U-shapes, but since  $B_{kt}$  is increasing in labor market experience  $t$ , older agents with the same belief as younger agents sort themselves into a lower occupation, yielding a downward drift. If that drift is too strong, then there will be no U-shapes if workers are paid their expected wage. This downward drift can be offset once accumulation of general human capital is introduced, since it induces an upward drift, yielding overall the potential for a balanced U-shape.

Based on wages according to (OA8), Gibbons, Katz, Lemieux, and Parent (2005) propose a method of quasi-differencing of the wages and using lagged occupational choices as instruments to estimate the underlying parameters. In this paper we provide evidence on mobility patterns and show that it is consistent with the type of selection that Gibbons, Katz, Lemieux, and Parent (2005) provide a method to control for. Since their method can be adapted to the setting in this paper, we view the two papers as complementary to each other.

# OA19 1, 2, 3, and 4-digit Occupational Classifications

MAJOR GROUP 1  
LEGISLATORS, SENIOR OFFICIALS AND MANAGERS  
11 LEGISLATORS AND SENIOR OFFICIALS  
111 LEGISLATORS  
1110 Legislators  
114 SENIOR OFFICIALS OF SPECIAL-INTEREST ORGANIZATIONS  
1141 Senior officials of political-party organizations  
1142 Senior officials of employers', workers' and other economic-interest organizations  
1143 Senior officials of humanitarian and other special-interest organizations  
12 CORPORATE MANAGERS (This group is intended to include persons who - as directors, chief executives or department managers - manage enterprises or organizations, or departments, requiring a total of three or more managers.)  
121 DIRECTORS AND CHIEF EXECUTIVES  
1210 Directors and chief executives  
122 PRODUCTION AND OPERATIONS DEPARTMENT MANAGERS  
1221 Production and operations department managers in agriculture, hunting, forestry and fishing  
1222 Production and operations department managers in manufacturing  
1223 Production and operations department managers in construction  
1224 Production and operations department managers in wholesale and retail trade  
1225 Production and operations department managers in restaurants and hotels  
1226 Production and operations department managers in transport, storage and communications  
1227 Production and operations department managers in business services  
1228 Production and operations department managers in personal care, cleaning and related services  
1229 Production and operations department managers not elsewhere classified  
123 OTHER DEPARTMENT MANAGERS  
1231 Finance and administration department managers  
1232 Personnel and industrial relations department managers  
1233 Sales and marketing department managers  
1234 Advertising and public relations department managers  
1235 Supply and distribution department managers  
1236 Computing services department managers  
1237 Research and development department managers  
1239 Other department managers not elsewhere classified  
13 GENERAL MANAGERS (This group is intended to include persons who manage enterprises, or in some cases organizations, on their own behalf, or on behalf of the proprietor, with some non-managerial help and the assistance of no more than one other manager who should also be classified in this sub- major group as, in most cases, the tasks will be broader than those of a specialized manager in a larger enterprise or organization. Non-managerial staff should be classified according to their specific tasks.)  
131 GENERAL MANAGERS  
1311 General managers in agriculture, hunting, forestry/ and fishing  
1312 General managers in manufacturing  
1313 General managers in construction  
1314 General managers in wholesale and retail trade  
1315 General managers of restaurants and hotels  
1316 General managers in transport, storage and communications  
1317 General managers of business services  
1318 General managers in personal care, cleaning and related services  
1319 General managers not elsewhere classified

MAJOR GROUP 2  
PROFESSIONALS  
21 PHYSICAL, MATHEMATICAL AND ENGINEERING SCIENCE PROFESSIONALS  
211 PHYSICISTS, CHEMISTS AND RELATED PROFESSIONALS  
2111 Physicists and astronomers  
2112 Meteorologists  
2113 Chemists  
2114 Geologists and geophysicists  
212 MATHEMATICIANS, STATISTICIANS AND RELATED PROFESSIONALS  
2121 Mathematicians and related professionals  
2122 Statisticians  
213 COMPUTING PROFESSIONALS  
2131 Computer systems designers and analysts  
2132 Computer programmers  
2139 Computing professionals not elsewhere classified  
214 ARCHITECTS, ENGINEERS AND RELATED PROFESSIONALS  
2141 Architects, town and traffic planners  
2142 Civil engineers  
2143 Electrical engineers  
2144 Electronics and telecommunications engineers  
2145 Mechanical engineers  
2146 Chemical engineers  
2147 Mining engineers, metallurgists and related professionals  
2148 Cartographers and surveyors  
2149 Architects, engineers and related professionals not elsewhere classified

22 LIFE SCIENCE AND HEALTH PROFESSIONALS  
221 LIFE SCIENCE PROFESSIONALS  
2211 Biologists, botanists, zoologists and related professionals  
2212 Pharmacologists, pathologists and related professionals  
2213 Agronomists and related professionals  
222 HEALTH PROFESSIONALS (except nursing)  
2221 Medical doctors  
2222 Dentists  
2223 Veterinarians  
2224 Pharmacists  
2229 Health professionals (except nursing) not elsewhere classified  
223 NURSING AND MIDWIFERY PROFESSIONALS  
2230 Nursing and midwifery professionals  
23 TEACHING PROFESSIONALS  
231 COLLEGE, UNIVERSITY AND HIGHER EDUCATION TEACHING PROFESSIONALS  
2310 College, university and higher education teaching professionals  
232 SECONDARY EDUCATION TEACHING PROFESSIONALS  
2320 Secondary education teaching professionals  
233 PRIMARY AND PRE-PRIMARY EDUCATION TEACHING PROFESSIONALS  
2331 Primary education teaching professionals  
234 SPECIAL EDUCATION TEACHING PROFESSIONALS  
2340 Special education teaching professionals  
235 OTHER TEACHING PROFESSIONALS  
2351 Education methods specialists  
2352 School inspectors  
2359 Other teaching professionals not elsewhere classified  
24 OTHER PROFESSIONALS  
241 BUSINESS PROFESSIONALS  
2411 Accountants  
2412 Personnel and careers professionals  
2419 Business professionals not elsewhere classified  
242 LEGAL PROFESSIONALS  
2421 Lawyers  
2422 Judges  
2429 Legal professionals not elsewhere classified  
243 ARCHIVISTS, LIBRARIANS AND RELATED INFORMATION PROFESSIONALS  
2431 Archivists and curators  
2432 Librarians and related information professionals  
244 SOCIAL SCIENCE AND RELATED PROFESSIONALS  
2441 Economists  
2442 Sociologists, anthropologists and related professionals  
2443 Philosophers, historians and political scientists  
2444 Philologists, translators and interpreters  
2445 Psychologists  
2446 Social work professionals  
245 WRITERS AND CREATIVE OR PERFORMING ARTISTS  
2451 Authors, journalists and other writers  
2452 Sculptors, painters and related artists  
2453 Composers, musicians and singers  
2454 Choreographers and dancers  
2455 Film, stage and related actors and directors  
246 RELIGIOUS PROFESSIONALS  
2460 Religious professionals  
2470: working with administration of legislation in the public sector

MAJOR GROUP 3  
TECHNICIANS AND ASSOCIATE PROFESSIONALS  
31 PHYSICAL AND ENGINEERING SCIENCE ASSOCIATE PROFESSIONALS  
311 PHYSICAL AND ENGINEERING SCIENCE TECHNICIANS  
3111 Chemical and physical science technicians  
3112 Civil engineering technicians  
3113 Electrical engineering technicians  
3114 Electronics and telecommunications engineering technicians  
3115 Mechanical engineering technicians  
3116 Chemical engineering technicians  
3117 Mining and metallurgical technicians  
3118 Draughtspersons  
3119 Physical and engineering science technicians not elsewhere classified  
312 COMPUTER ASSOCIATE PROFESSIONALS  
3121 Computer assistants  
3122 Computer equipment operators  
3123 Industrial robot controllers  
313 OPTICAL AND ELECTRONIC EQUIPMENT OPERATORS  
3131 Photographers and image and sound recording equipment operators  
3132 Broadcasting and telecommunications equipment operators  
3133 Medical equipment operators  
3139 Optical and electronic equipment operators not elsewhere classified  
314 SHIP AND AIRCRAFT CONTROLLERS AND TECHNICIANS  
3141 Ships' engineers  
3142 Ships' deck officers and pilots  
3143 Aircraft pilots and related associate professionals  
3144 Air traffic controllers

3145 Air traffic safety technicians  
315 SAFETY AND QUALITY INSPECTORS  
3151 Building and fire inspectors 3152 Safety, health and quality inspectors  
32 LIFE SCIENCE AND HEALTH ASSOCIATE PROFESSIONALS  
321 LIFE SCIENCE TECHNICIANS AND RELATED ASSOCIATE PROFESSIONALS  
3211 Life science technicians  
3212 Agronomy and forestry technicians  
3213 Farming and forestry advisers  
322 MODERN HEALTH ASSOCIATE PROFESSIONALS (except nursing)  
3221 Medical assistants  
3222 Sanitarians  
3223 Dietitians and nutritionists  
3224 Optometrists and opticians  
3225 Dental assistants  
3226 Physiotherapists and related associate professionals  
3227 Veterinary assistants  
3228 Pharmaceutical assistants  
3229 Modern health associate professionals (except nursing) not elsewhere classified  
323 NURSING AND MIDWIFERY ASSOCIATE PROFESSIONALS  
3231 Nursing associate professionals  
33 TEACHING ASSOCIATE PROFESSIONALS  
331 PRIMARY EDUCATION TEACHING ASSOCIATE PROFESSIONALS  
3310 Primary education teaching associate professionals  
332 PRE-PRIMARY EDUCATION TEACHING ASSOCIATE PROFESSIONALS  
3320 Pre-primary education teaching associate professionals  
333 SPECIAL EDUCATION TEACHING ASSOCIATE PROFESSIONALS  
3330 Special education teaching associate professionals  
334 OTHER TEACHING ASSOCIATE PROFESSIONALS  
3340 Other teaching associate professionals  
34 OTHER ASSOCIATE PROFESSIONALS  
341 FINANCE AND SALES ASSOCIATE PROFESSIONALS  
3411 Securities and finance dealers and brokers  
3412 Insurance representatives  
3413 Estate agents  
3414 Travel consultants and organizers  
3415 Technical and commercial sales representatives  
3416 Buyers  
3417 Appraisers, valuers and auctioneers  
3419 Finance and sales associate professionals not elsewhere classified  
342 BUSINESS SERVICES AGENTS AND TRADE BROKERS  
3421 Trade brokers  
3422 Clearing and forwarding agents  
3423 Employment agents and labor contractors  
3429 Business services agents and trade brokers not elsewhere classified  
343 ADMINISTRATIVE ASSOCIATE PROFESSIONALS  
3431 Administrative secretaries and related associate professionals  
3432 Legal and related business associate professionals  
3433 Bookkeepers  
3434 Statistical, mathematical and related associate professionals  
3439 Administrative associate professionals not elsewhere classified  
344 CUSTOMS, TAX AND RELATED GOVERNMENT ASSOCIATE PROFESSIONALS  
3441 Customs and border inspectors  
3442 Government tax and excise officials  
3443 Government social benefits officials  
3444 Government licensing officials  
3449 Customs, tax and related government associate professionals not elsewhere classified  
345 POLICE INSPECTORS AND DETECTIVES  
3450 Police inspectors and detectives  
346 SOCIAL WORK ASSOCIATE PROFESSIONALS  
3460 Social work associate professionals  
347 ARTISTIC, ENTERTAINMENT AND SPORTS ASSOCIATE PROFESSIONALS  
3471 Decorators and commercial designers  
3472 Radio, television and other announcers  
3473 Street, night-club and related musicians, singers and dancers  
3474 Clowns, magicians, acrobats and related associate professionals  
3475 Athletes, sportspersons and related associate professionals  
348 RELIGIOUS ASSOCIATE PROFESSIONALS  
3480 Religious associate professionals

#### MAJOR GROUP 4 CLERKS

41 OFFICE CLERKS  
411 SECRETARIES AND KEYBOARD-OPERATING CLERKS  
4111 Stenographers and typists  
4112 Word-processor and related operators  
4113 Data entry operators  
4114 Calculating-machine operators  
4115 Secretaries  
412 NUMERICAL CLERKS  
4121 Accounting and bookkeeping clerks  
4122 Statistical and finance clerks  
413 MATERIAL-RECORDING AND TRANSPORT CLERKS  
4131 Stock clerks  
4132 Production clerks  
4133 Transport clerks  
414 LIBRARY, MAIL AND RELATED CLERKS

4141 Library and filing clerks  
4142 Mail carriers and sorting clerks  
4143 Coding, proof-reading and related clerks  
419 OTHER OFFICE CLERKS  
4190 Other office clerks  
42 CUSTOMER SERVICES CLERKS  
421 CASHIERS, TELLERS AND RELATED CLERKS  
4211 Cashiers and ticket clerks  
4212 Tellers and other counter clerks  
4213 Bookmakers and croupiers  
4214 Pawnbrokers and money-lenders  
4215 Debt-collectors and related workers  
422 CLIENT INFORMATION CLERKS  
4221 Travel agency and related clerks  
4222 Receptionists and information clerks  
4223 Telephone switchboard operators

#### MAJOR GROUP 5

SERVICE WORKERS AND SHOP AND MARKET SALES WORKERS  
51 PERSONAL AND PROTECTIVE SERVICES WORKERS  
511 TRAVEL ATTENDANTS AND RELATED WORKERS  
5111 Travel attendants and travel stewards  
5112 Transport conductors  
5113 Travel guides  
512 HOUSEKEEPING AND RESTAURANT SERVICES WORKERS  
5121 Housekeepers and related workers  
5122 Cooks  
5123 Waiters, waitresses and bartenders  
513 PERSONAL CARE AND RELATED WORKERS  
5131 Child-care workers  
5132 Institution-based personal care workers  
5133 Home-based personal care workers  
5139 Personal care and related workers not elsewhere classified  
514 OTHER PERSONAL SERVICES WORKERS  
5141 Hairdressers, barbers, beauticians and related workers  
5142 Companions and valets  
5143 Undertakers and embalmers  
5149 Other personal services workers not elsewhere classified  
515 ASTROLOGERS, FORTUNE-TELLERS AND RELATED WORKERS  
5151 Astrologers and related workers  
5152 Fortune-tellers, palmists and related workers  
516 PROTECTIVE SERVICES WORKERS  
5161 Fire-fighters  
5162 Police officers  
5163 Prison guards  
5169 Protective services workers not elsewhere classified  
52 MODELS, SALESPERSONS AND DEMONSTRATORS  
521 FASHION AND OTHER MODELS  
5210 Fashion and other models  
522 SHOP SALESPERSONS AND DEMONSTRATORS  
5220 Shop salespersons and demonstrators  
523 STALL AND MARKET SALESPERSONS  
5230 Stall and market salespersons

#### MAJOR GROUP 6

SKILLED AGRICULTURAL AND FISHERY WORKERS  
61 MARKET-ORIENTED SKILLED AGRICULTURAL AND FISHERY WORKERS  
611 MARKET GARDENERS AND CROP GROWERS  
6111 Field crop and vegetable growers  
6112 Tree and shrub crop growers  
612 MARKET-ORIENTED ANIMAL PRODUCERS AND RELATED WORKERS  
6121 Dairy and livestock producers  
6122 Poultry producers  
6129 Market-oriented animal producers and related workers not elsewhere classified  
613 MARKET-ORIENTED CROP AND ANIMAL PRODUCERS  
6130 Market-oriented crop and animal producers  
614 FORESTRY AND RELATED WORKERS  
6141 Forestry workers and loggers  
6142 Charcoal burners and related workers  
615 FISHERY WORKERS, HUNTERS AND TRAPPERS  
6151 Aquatic-life cultivation workers  
6152 Inland and coastal waters fishery workers  
6153 Deep-sea fishery workers  
6154 Hunters and trappers

#### MAJOR GROUP 7

CRAFT AND RELATED TRADES WORKERS  
71 EXTRACTION AND BUILDING TRADES WORKERS  
711 MINERS, SHOTFIRERS, STONE CUTTERS AND CARVERS  
7111 Miners and quarry workers  
7112 Shotfirers and blasters  
7113 Stone splitters, cutters and carvers  
712 BUILDING FRAME AND RELATED TRADES WORKERS  
7121 Builders, traditional materials  
7122 Bricklayers and stonemasons  
7123 Concrete placers, concrete finishers and related workers  
7124 Carpenters and joiners  
7129 Building frame and related trades workers not elsewhere classified  
713 BUILDING FINISHERS AND RELATED TRADES WORKERS



7131 Roofers  
 7132 Floor layers and tile setters  
 7133 Plasterers  
 7134 Insulation workers  
 7135 Glaziers  
 7136 Plumbers and pipe fitters  
 7137 Building and related electricians  
 7139 Buildingswork elsewhere  
 714 PAINTERS, BUILDING STRUCTURE CLEANERS AND RELATED TRADES WORKERS  
 7141 Painters and related workers  
 7142 Varnishers and related painters  
 7143 Building structure cleaners  
 72 METAL, MACHINERY AND RELATED TRADES WORKERS  
 721 METAL MOULDERS, WELDERS, SHEET-METAL WORKERS, STRUCTURAL- METAL PREPARERS, AND RELATED TRADES WORKERS  
 7211 Metal moulders and coremakers  
 7212 Welders and flamecutters  
 7213 Sheet metal workers  
 7214 Structural-metal preparers and erectors  
 7215 Riggers and cable splicers  
 7216 Underwater workers  
 722 BLACKSMITHS, TOOL-MAKERS AND RELATED TRADES WORKERS  
 7221 Blacksmiths, hammer-smiths and forging-press workers  
 7222 Tool-makers and related workers  
 7223 Machine-tool setters and setter-operators  
 7224 Metal wheel-grinders, polishers and tool sharpeners  
 723 MACHINERY MECHANICS AND FITTERS  
 7231 Motor vehicle mechanics and fitters  
 7232 Aircraft engine mechanics and fitters  
 7233 Agricultural- or industrial-machinery mechanics and fitters  
 724 ELECTRICAL AND ELECTRONIC EQUIPMENT MECHANICS AND FITTERS  
 7241 Electrical mechanics and fitters  
 7242 Electronics fitters  
 7243 Electronics mechanics and servicers  
 7244 Telegraph and telephone installers and servicers  
 7245 Electrical line installers, repairers and cable jointers  
 73 PRECISION, HANDICRAFT, PRINTING AND RELATED TRADES WORKERS  
 731 PRECISION WORKERS IN METAL AND RELATED MATERIALS  
 7311 Precision-instrument makers and repairers  
 7312 Musical instrument makers and tuners  
 7313 Jewellery and precious-metal workers  
 732 POTTERS, GLASS-MAKERS AND RELATED TRADES WORKERS  
 7321 Abrasive wheel formers, potters and related workers  
 7322 Glass makers, cutters, grinders and finishers  
 7323 Glass engravers and etchers  
 7324 Glass, ceramics and related decorative painters  
 733 HANDICRAFT WORKERS IN WOOD, TEXTILE, LEATHER AND RELATED MATERIALS  
 7331 Handicraft workers in wood and related materials  
 7332 Handicraft workers in textile, leather and related materials  
 734 PRINTING AND RELATED TRADES WORKERS  
 7341 Compositors, typesetters and related workers  
 7342 Stereotypers and electrotypers  
 7343 Printing engravers and etchers  
 7344 Photographic and related workers  
 7345 Bookbinders and related workers  
 7346 Silk-screen, block and textile printers  
 74 OTHER CRAFT AND RELATED TRADES WORKERS  
 741 FOOD PROCESSING AND RELATED TRADES WORKERS  
 7411 Butchers, fishmongers and related food preparers  
 7412 Bakers, pastry-cooks and confectionery makers  
 7413 Dairy-products makers  
 7414 Fruit, vegetable and related preservers  
 7415 Food and beverage tasters and graders  
 7416 Tobacco preparers and tobacco products makers  
 742 WOOD TREATERS, CABINET-MAKERS AND RELATED TRADES WORKERS  
 7421 Wood treaters  
 7422 Cabinet makers and related workers  
 7423 Woodworking machine setters and setter-operators  
 7424 Basketry weavers, brush makers and related workers  
 743 TEXTILE, GARMENT AND RELATED TRADES WORKERS  
 7431 Fiber preparers  
 7432 Weavers, knitters and related workers  
 7433 Tailors, dressmakers and hatters  
 7434 Furriers and related workers  
 7435 Textile, leather and related pattern-makers and cutters  
 7436 Sewers, embroiderers and related workers  
 7437 Upholsterers and related workers  
 744 PELT, LEATHER AND SHOEMAKING TRADES WORKERS  
 7441 Pelt dressers, tanners and fellmongers  
 7442 Shoe-makers and related workers  
 8 MAJOR GROUP 8  
 PLANT AND MACHINE OPERATORS AND ASSEMBLERS  
 81 STATIONARY-PLANT AND RELATED OPERATORS  
 811 MINING- AND MINERAL-PROCESSING-PLANT OPERATORS  
 8111 Mining-plant operators  
 8112 Mineral-ore- and stone-processing-plant operators  
 8113 Well drillers and borers and related workers  
 812 METAL-PROCESSING-PLANT OPERATORS  
 8121 Ore and metal furnace operators  
 8122 Metal melters, casters and rolling-mill operators  
 8123 Metal-heat-treating-plant operators  
 8124 Metal drawers and extruders  
 813 GLASS, CERAMICS AND RELATED PLANT OPERATORS  
 8131 Glass and ceramics kiln and related machine operators  
 8139 Glass, ceramics and related plant operators not elsewhere classified  
 814 WOOD-PROCESSING- AND PAPERMAKING-PLANT OPERATORS  
 8141 Wood-processing-plant operators  
 8142 Paper-pulp plant operators  
 8143 Papermaking-plant operators  
 815 CHEMICAL-PROCESSING-PLANT OPERATORS  
 8151 Crushing-, grinding- and chemical-mixing-machinery operators  
 8152 Chemical-heat-treating-plant operators  
 8153 Chemical-filtering- and separating-equipment operators  
 8154 Chemical-still and reactor operators (except petroleum and natural gas)  
 8155 Petroleum- and natural-gas-refining-plant operators  
 8159 Chemical-processing-plant operators not elsewhere classified  
 816 POWER-PRODUCTION AND RELATED PLANT OPERATORS  
 8161 Power-production plant operators  
 8162 Steam-engine and boiler operators  
 8163 Incinerator, water-treatment and related plant operators  
 817 AUTOMATED-ASSEMBLY-LINE AND INDUSTRIAL-ROBOT OPERATORS  
 82 MACHINE OPERATORS AND ASSEMBLERS  
 821 METAL- AND MINERAL-PRODUCTS MACHINE OPERATORS  
 8211 Machine-tool operators  
 8212 Cement and other mineral products machine operators  
 822 CHEMICAL-PRODUCTS MACHINE OPERATORS  
 8221 Pharmaceutical- and toiletry-products machine operators  
 8222 Ammunition- and explosive-products machine operators  
 8223 Metal finishing-, plating- and coating-machine operators  
 8224 Photographic-products machine operators  
 8229 Chemical-products machine operators not elsewhere classified  
 823 RUBBER- AND PLASTIC-PRODUCTS MACHINE OPERATORS  
 8231 Rubber-products machine operators  
 8232 Plastic-products machine operators  
 824 WOOD-PRODUCTS MACHINE OPERATORS  
 8240 Wood-products machine operators  
 825 PRINTING-, BINDING- AND PAPER-PRODUCTS MACHINE OPERATORS  
 8251 Printing-machine operators  
 8252 Bookbinding-machine operators  
 8253 Paper-products machine operators  
 826 TEXTILE-, FUR- AND LEATHER-PRODUCTS MACHINE OPERATORS  
 8261 Fiber-preparing-, spinning- and winding-machine operators  
 8262 Weaving- and knitting-machine operators  
 8263 Sewing-machine operators  
 8264 Bleaching-, dyeing- and cleaning-machine operators  
 8265 Fur and leather-preparing-machine operators  
 8266 Shoemaking- and related machine operators  
 8269 Textile-, fur- and leather-products machine operators not elsewhere classified  
 827 FOOD AND RELATED PRODUCTS MACHINE OPERATORS  
 8271 Meat- and fish-processing-machine operators  
 8272 Dairy-products machine operators  
 8273 Grain- and spice-milling-machine operators  
 8274 Baked-goods, cereal and chocolate-products machine operators  
 8275 Fruit-, vegetable- and nut-processing-machine operators  
 8276 Sugar production machine operators  
 8277 Tea-, coffee-, and cocoa-processing-machine operators  
 8278 Brewers, wine and other beverage machine operators  
 8279 Tobacco production machine operators  
 828 ASSEMBLERS  
 8281 Mechanical-machinery assemblers  
 8282 Electrical-equipment assemblers  
 8283 Electronic-equipment assemblers  
 8284 Metal-, rubber- and plastic-products assemblers  
 8285 Wood and related products assemblers  
 8286 Paperboard, textile and related products assemblers  
 8287: Assembly line and assembler elsewhere  
 829 OTHER MACHINE OPERATORS AND ASSEMBLERS  
 8290 Other machine operators and assemblers  
 83 DRIVERS AND MOBILE-PLANT OPERATORS  
 831 LOCOMOTIVE-ENGINE DRIVERS AND RELATED WORKERS  
 8311 Locomotive-engine drivers  
 8312 Railway brakemen, signallers and shunters  
 832 MOTOR-VEHICLE DRIVERS  
 8321 Motor-cycle drivers  
 8322 Car, taxi and van drivers  
 8323 Bus and tram drivers  
 8324 Heavy-truck and lorry drivers  
 833 AGRICULTURAL AND OTHER MOBILE-PLANT OPERATORS  
 8331 Motorized farm and forestry plant operators  
 8332 Earth-moving- and related plant operators  
 8333 Crane, hoist and related plant operators

8334 Lifting-truck operators  
834 SHIPS' DECK CREWS AND RELATED WORKERS  
8340 Ships' deck crews and related workers

MAJOR GROUP 9

ELEMENTARY OCCUPATIONS

91 SALES AND SERVICES ELEMENTARY OCCUPATIONS

911 STREET VENDORS AND RELATED WORKERS

9113 Door-to-door and telephone salespersons

912 SHOE CLEANING AND OTHER STREET SERVICES ELEMENTARY OCCUPATIONS

9120 Shoe cleaning and other street services elementary occupations

913 DOMESTIC AND RELATED HELPERS, CLEANERS AND LAUNDERERS

9131 Domestic helpers and cleaners

9132 Helpers and cleaners in offices, hotels and other establishments

9133 Hand-launders and pressers

914 BUILDING CARETAKERS, WINDOW AND RELATED CLEANERS

9141 Building caretakers

9142 Vehicle, window and related cleaners

915 MESSENGERS, PORTERS, DOORKEEPERS AND RELATED WORKERS

9151 Messengers, package and luggage porters and deliverers

9152 Doorkeepers, watchpersons and related workers

9153 Vending-machine money collectors, meter readers and related workers

916 GARBAGE COLLECTORS AND RELATED LABORERS

9161 Garbage collectors

9162 Sweepers and related laborers

92 AGRICULTURAL, FISHERY AND RELATED LABORERS

921 AGRICULTURAL, FISHERY AND RELATED LABORERS

9211 Farm-hands and laborers

9212 Forestry laborers

9213 Fishery, hunting and trapping laborers

93 LABORERS IN MINING, CONSTRUCTION, MANUFACTURING AND TRANSPORT

931 MINING AND CONSTRUCTION LABORERS

9311 Mining and quarrying laborers

9312 Construction and maintenance laborers: roads, dams and similar constructions

9313 Building construction laborers

932 MANUFACTURING LABORERS

933 TRANSPORT LABORERS AND FREIGHT HANDLERS

MAJOR GROUP 0

ARMED FORCES

01 ARMED FORCES

011 ARMED FORCES

0110 Armed forces